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Risk Analysis of Operational Disruptions in Public Electric Vehicle Charging Stations Using the Failure Mode and Effects Analysis (FMEA) Method

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Abstract

The Indonesia government is actively promoting the adoption of electric vehicles, as detailed in the 2021-2030 Electricity Supply Business Plan. The state-owned electricity provider, PLN, is responsible for establishing Public Electric Vehicle Charging Stations (PEVCS). However, several of these stations have encountered malfunctions; notably, 82 of the 567 stations are classified as Unavailable, indicating they are non-functional. Research literature points to a financial loss of $34,000 from operational issues at PEVCSs. This research aims to helps management understand and prioritize disruption that leads to failures or damages at these stations. Method used is the Failure Mode and Effects Analysis (FMEA) method along with logistic regression to examine the disruptions at PEVCSs labeled as Unavailable. The data for this research comes from a six-month historical record of PEVCS disruptions. The variables utilized for logistic regression analysis include foundational variables from the FMEA methodology—Severity, Occurrence, and Disturbance—complemented by two supplementary variables: the speed and age of the PEVCS. Result was found that three out of twelve types of disruptions have a high likelihood of failure, specifically issues with Device Communication, Connectivity, and Emergency Stop functions. A disruption is deemed likely to cause failure if its probability exceeds 50%.

Keywords: PEVCS, FMEA, Disruptive mitigation.

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1. Introduction

Over the past decade, electric vehicles (EVs) have experienced a substantial increase in demand due to their ability to significantly decrease CO2 emissions and their lower operating costs compared to traditional internal combustion engines (Parker et al., 2021). This surge in adoption is underscored by the registration of over 5 million electric vehicles globally (Hasan et al., 2021). Despite the advantages of battery electric vehicles, they face significant challenges, including the high cost of electric vehicles and the scarcity of charging stations, specifically Public Electric Vehicle Charging Stations (PEVCS). The availability of dependable charging infrastructure is essential for the efficient operation of electric vehicles, especially given the rarity and extended duration required to charge an EV (Ahmad & Bilal, 2023). The government has assigned PT PLN the responsibility of quickly increasing the availability of PEVCSs across Indonesia.

PT PLN (Persero) is a government-owned electricity company mandated through the Electricity Supply Business Plan (RUPTL) for 2021-2030 to accelerate the setup of PEVCSs. The government's objective includes establishing 48,118 PEVCSs and 196,179 Public Electric Vehicle Battery Swap Stations (SPBKLU) by 2030. Data from the PLN's Internal Monitoring System for November 2023 shows that there are currently 567 PEVCSs in Indonesia. According to Table 1.1, 484 PEVCSs are operational (85% of the total), 82 are not in service (14% of the total), and one is under maintenance. An Unavailable status indicates that the PEVCS is out of operation due to malfunctions. PLN is actively addressing these issues by working with manufacturers to repair the affected units to ensure they are functional again.

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Table 1.1. Status of Installed PLN PEVCSs

UNIT	AVAILABLE	UNAVAILABLE	MAINTENANCE	TOTAL
ACEH	4	0	0	4
SUMATERA UTARA	13	2	1	16
SUMATERA BARAT	4	0	0	4
S2JB	13	4	0	17
BANGKA BELITUNG	4	0	0	4
LAMPUNG	9	2	0	11
WRKR	5	0	0	5
KALIMANTAN BARAT	6	3	0	9
KALSELTENG	10	0	0	10
KALTIMRA	11	4	0	15
SULUTTENGGO	8	2	0	10
SULSELRABAR	15	2	0	17
MALUKU & MALUKU UTARA	2	2	0	4
PAPUA & PAPUA BARAT	3	1	0	4
NUSA TENGGARA TIMUR	4	8	0	12
NUSA TENGGARA BARAT	9	4	0	13
JAWA TIMUR	53	6	0	59
JAWA TENGAH DAN DIY	47	1	0	48
JAWA BARAT	117	28	0	145
JAKARTA RAYA	64	9	0	73
BALI	60	3	0	63
BANTEN	23	1	0	24
HOLDING	484	82	1	567

Operational issues significantly affect the electrical system's performance, including power quality degradation, equipment failure, and consumer service disruptions. (Łukasik & Olczykowski, 2020) emphasize that disruptions in power quality and interruptions in supply can lead to financial losses and pose serious safety risks to people. Failures in electrical equipment can critically endanger the safety of the power network, making it crucial to perform regular inspections and evaluations to maintain a safe and reliable network operation (Li Ming-l, 2015). Reducing the risk associated with operational disturbances in the electrical system can be achieved through regular maintenance. According to (Gong et al., 2019), maintenance is critical to the lifecycle of electric vehicle charging stations, and their findings indicate that PEVCSs require maintenance seven times to maintain optimal operational reliability and efficiency.

Disruptions at PEVCS can stem from various causes such as short circuits leading to damage to the electronics at the PEVCS and the vehicle's battery (Hesami et al., 2021), overheating in the connector between the PEVCS charging cable and the vehicle's inlet which damages the plastic couplings at both connection ends (Reid, P., et al.), and conductive electromagnetic disturbances that degrade overall power quality (Mazurek & Chudy, 2022), among other issues. Disruptions can have serious operational consequences, resulting in significant losses (Chen et al., 2023). Research indicates that operational costs due to disruptions can be as high as $25,000 with a reliability coefficient of 0.5, decreasing as the PEVCS's reliability coefficient improves. Failures at stations can also incur penalties up to $9,000 (under the Robust-DF approach), highlighting the substantial economic impact of PEVCS damage and the necessity for proactive risk mitigation strategies against potential disruptions.

The conventional method for operational risk assessment is the Failure Mode and Effects Analysis (FMEA), which is a systematic approach to identify potential failures and associated risks (Y. Liu et al., 2018; Schneider, 1996). The result of an FMEA is expressed as a Risk Priority Number (RPN), calculated by multiplying variables related to impact (severity), frequency (occurrence), and detection, which together signal a higher level of risk. These variable values are obtained from expert evaluations in the researched field. However, journals often integrate FMEA with other methods such as logistic regression (Bhattacharjee et al., 2020), Bow Tie Analysis (Ambarwati et al., 2022) and more, as RPN on its own is seen as inflexible and sometimes challenging to implement practically (Bhattacharjee et al., 2020). In PEVCS contexts, one study by (Parkash et al., n.d.) employed FMEA based on complaints from electric vehicle users, not on PEVCS's historical disruptions. This study, therefore, seeks to apply FMEA based on historical disruptions at PEVCSs and also uses logistic regression to identify which variables critically influence an PEVCS's failure.

This research aims to quantify the likelihood of failures leading to PEVCSs being classified as Unavailable to minimize the risk of damage in PEVCSs. The soutcomes are expected to provide valuable insights for PT PLN to enhance the preparedness and reliability of PEVCSs based on adjusted risk analysis. Additionally, for external entities or those outside of PT PLN, the findings can be utilized as a reference to gauge the failure probabilities of various disruptions.

2. Literature Review

Electric vehicle usage has surged as they are increasingly viewed as viable alternatives to internal combustion engines (ICE), evidenced by over 5 million electric vehicles (EVs) registered globally (Hasan et al., 2021; Parker et al., 2021). This shift is bolstered by the support from authorities in numerous developing countries who advocate for electric vehicles to cut down on pollutants like carbon dioxide and other greenhouse gases (Tiwari et al., 2023). Electric vehicles are powered by electricity and come in three types: battery electric vehicles, plug-in hybrid electric vehicles, and hybrid electric vehicles (Kettles et al., 2016). The rise in electric vehicle adoption offers multiple advantages including (i) less reliance on oil and reduced gas emissions, (ii) a decrease in the carbon footprint aiding carbon neutrality, (iii) the promotion of a green transportation revolution, and the potential to mitigate climate change (W. Liu et al., 2022). All three types of EV use charging stations to charge their batteries, whether using private (home charging) or public charging station.

Public Electric Vehicle Charging Stations (PEVCS) are parking areas that can be public or private, equipped with the necessary infrastructure to provide power for charging electric vehicles. These stations include essential amenities such as information signs, pedestrian paths, surfacing, billing systems, and safety equipment for vehicle charging (Na & Hipertensiva, 2019). The expansion of PEVCSs by PLN is in line with Presidential Regulation Number 55 of 2019, which is focused on encouraging the use of battery electric vehicles (BEV) within the nation's electric transportation network, while still taking into account existing conditions and risks.

The additional variables included in this research are charging speed and the age of the PEVCS. The speed of charging at PEVCSs is essential for determining the convenience and practicality of using Battery Electric Vehicles (BEV). Presently, there are three main levels of charging stations utilized: Level 1, 2, and 3, also commonly referred to as fast charging, as highlighted by (Khalid et al., 2019). The quicker the charging process, the shorter the waiting time required for users. Research by Wolbertus et al., 2018 shows that the time taken to charge and the type of charging station significantly affect usage factors at charging stations. Based on that previous research, variable charging speed is added as variable in this research. In Indonesia, the Ministry of Energy and Mineral Resources (ESDM) regulates the levels of charging speeds. As per Minister of ESDM Regulation No. 1 of 2023, Article 1, PEVCS charging speeds in Indonesia are standardized into four categories: Slow Charging Technology, which allows for charging up to 7 kW; Medium Charging Technology, which supports charging capacities from over 7 kilowatts up to 22 kilowatts; Fast Charging Technology, enabling charging from over 22 kilowatts up to 50 kilowatts; and Ultrafast Charging Technology, which provides charging capabilities exceeding 50 kilowatts.

The second additional variable is PEVCS' age. Shi et al. (2022) discovered that consumer behavior plays a crucial role in deciding the duration a product is used before it is replaced or discarded. In the case of Electric Vehicle Charging Stations (PEVCS), the users of these stations and PLN, the product owner, are considered consumers. Additionally, (Wang et al., 2019) highlighted that the lifespan of PEVCS impacts the risk of voltage exposure to customers during the electric vehicle charging process.

Risk is defined as the potential for loss, indicating that there is a likelihood of an event or incident occurring on a scale from zero (no occurrence) to one (certain occurrence) (Darmawi, 2005). Typically, this risk refers to possible events that may adversely affect an entity's objectives, whether the entity operates for profit or not. Broadly, risk encompasses any factor that could result in a loss for a company or organization. Risk is broadly categorized under three main headings as specified by Pillar I of the New Basel Capital Accord: Market Risk, Credit Risk and Operational Risk. In this research context, disruption on PEVCS can be categorized in Operational Risk. (Crouhy et al., n.d.) describes operational risk as potential losses resulting from inadequate systems, management failures, insufficient control measures, fraud, and human mistakes. Some of these losses can be effectively foreseen and managed, whereas others may not be predicted at all. Chapman (2006) emphasizes the importance of risk management as it enhances service delivery, improves resource utilization, better manages projects, and helps reduce waste, fraud, devaluation of money, and fosters innovation. The core activities in operational risk management involve identifying operational risks, assessing or measuring these risks, responding to them, and monitoring and controlling operational risks.

To understand the risk of PEVCS disruption, this research collects many PEVCS disruptions from available journals, the table 1.

Table 2. The study about PEVCS Disruptions

Disruption	Cause	Effect	Preventive and Corrective	Reference
Obsolete Part	Failure to replace parts that are either worn out or outdated	Increased downtime, reduced reliability of the charging service, potential safety hazards due to malfunctioning parts, and ultimately, customer dissatisfaction.	Regular maintenance schedules should be strictly followed. Worn out or outdated parts should be identified and replaced promptly. The use of a robust monitoring system to track the status and performance of all critical components can also help in timely identification and replacement of such parts	(Wang et al., 2019)
Harmonic Injection, Excessive Current, and Voltage Deviation	Imbalance between demand and supply in the electrical grid.	Degradation of power quality, distribution transformer overloading, charging stations becoming inactive.	Implementation of IEEE and IEC power quality standards.	(Khalid et al., 2019)
Voltage Drop	High power demand for electric vehicle charging that can exceed the capacity of the local network.	Damage to other electrical equipment connected to the same network, which can also affect the EV charging process itself.	Implementation of a Dynamic Voltage Restorer (DVR) system to compensate for voltage drops.	(Lei et al., 2019)
Emergency stop	Failures in the PEVCS system and damage to its mechanical or electronic components.	The unit ceases functioning and could potentially harm the battery or the vehicle.	Conduct regular maintenance, outline safety protocols, and offer education to both users and staff.	(Li et al., 2021)

Disruption	Cause	Effect	Preventive and Corrective	Reference
Conductive Electromagnetic Interference (EMI).	The fast-acting converters used in public electric vehicle charging stations can generate high-frequency noise, potentially causing issues for both the power grid and communication networks.	Issues like inefficiency or malfunction during charging can bring down the overall quality of the power being delivered.	To ensure electromagnetic compatibility (EMC), various techniques can be used include controlling where the interference comes from, properly grounding the system, using shields to block electromagnetic waves, and implementing isolation technology to separate different parts of the system.	(Mazurek & Chudy, 2022)
Critical Voltage Disturbance	Voltage swings caused by the unpredictable nature of EV charging and renewable energy.	Ineffective charging and potential damage to batteries and charging systems	The application of disturbance observer-based predictive voltage control	Kim, D.-J., et al. (2023)
High Voltage Disturbance	Peak load increases due to fast charging stations	Reduced reserve margin, decreased voltage stability, and reliability issues in the electricity distribution network	Optimization of the placement and sizing of fast charging stations	Sadeghi-Barzani, P., et al. (2014)
Short Circuit	Short Circuit	Damage to electronic equipment on the EV charging station (PEVCS) side and batteries on the electric vehicle (EV) side	Enhancing the resilience of the distribution system against short-circuit faults by employing robust protection mechanisms.	(Hesami et al., 2021)
Cyberattacks and Infrastructure Damage	Infrastructure degradation, cyberattacks, and the mismatch between renewable energy output and EV charging demand.	Has the potential to disrupt the operational security of large-scale EV charging stations.	Regular maintenance of facilities and enhanced cyber security.	(Wang et al., 2019)

Disruption	Cause	Effect	Preventive and Corrective	Reference
Rise in temperature at the charging connection	Rise in temperature at the connector between the PEVCS charging cable and the vehicle inlet	Damage to the plastic coupling housings on both sides of the connection	Utilizing heat-resistant materials and designing more efficient connectors.	Reid, P., et al. (2014)

2.1. Failure Mode and Effect Analysis

Failure Mode and Effects Analysis (FMEA) is an engineering approach designed to detect, identify, and eradicate both known and potential failures, issues, and errors from systems, designs, processes, or services before they impact the customer. This analytical process can follow two methodologies. Initially, one can utilize historical data to analyze similar products or services, encompassing warranty information, customer complaints, and other pertinent data to pinpoint failures. Alternatively, methods like inferential statistics, mathematical models, simulations, concurrent engineering, and reliability engineering are employed to identify and describe failures (Schneider, 1996).

The application of FMEA doesn't inherently favor one methodology over another, nor does it imply that one is more precise. Both strategies can be effective and accurate when implemented correctly. When executed properly, FMEA furnishes practitioners with crucial information that helps minimize risks in systems, designs, processes, and services. It is recognized for its systematic and progressive approach to potential failure analysis, enhancing the efficacy of task performance. FMEA serves as a crucial preventive measure in systems, designs, processes, and services to avert failures and errors from reaching the customer (Schneider, 1996).

This technique of early detection and prevention allows designers to methodically explore the causes and consequences of failures before finalizing a system, design, process, or service. Fundamentally, FMEA offers a systematic way to explore all possible failure modes. For each identified failure, impacts on the entire system, severity (S), frequency (F), and detection (D) are assessed.

(Schneider, 1996) highlights that FMEA pinpoints necessary corrective measures to stop failures from reaching customers, thereby ensuring optimal durability, quality, and reliability in products or services. A well-conducted FMEA will identify all known and potential failure modes, determine the causes and effects associated with each failure mode

Rank failure modes by their Risk Priority Number (RPN), which is calculated based on the frequency of occurrence, severity, and detection, manage issue follow-ups and corrective actions.

3. Methods

This study utilizes the FMEA (Failure Mode and Effect Analysis) methodology, a systematic approach for identifying potential failures and associated risks (Schneider, 1996). In FMEA, risks of potential failures are initially assessed using three factors: Occurrence (O), Severity (S), and Detection (D). O evaluates the likelihood of failure, S gauges the impact of the failure, and D assesses the chance of detecting the failure. The Risk Priority Number (RPN) is calculated by considering high S, high O, and low D, indicating a higher risk level. However, (Bhattacharjee et al., 2020) suggested that additional factors beyond S, O, and D could affect failure risk, and they applied logistic regression to achieve a more comprehensive analysis of failures. The integration of FMEA and logistic regression is illustrated in figure 1.

Figure 1 illustrates that the traditional FMEA typically uses only three variables: Severity (S), Occurrence (O), and Detection (D). This method is commonly applied to analyze disruptions. The FMEA outcome is an expert's evaluation of a case, represented by a combined score of these three variables, called the Risk Priority Number (RPN). However, Bhattacharjee et al. (2020) identified the necessity of incorporating additional variables for enhanced accuracy. In this study, the extra variables included are the charging speed and lifespan of PEVCS. These two additional factors are integrated into the expert assessment, resulting in five independent variables and one expert opinion on failures, which serves as the dependent variable. Following the expert evaluation, logistic regression is used to identify which variables influence PEVCS failures.

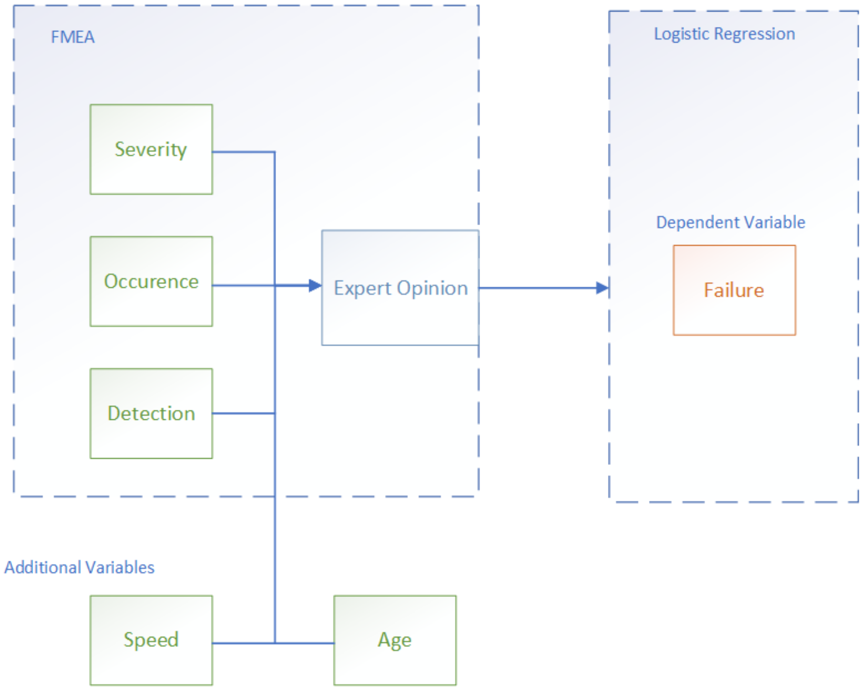

Figure 1. Framework for combining FMEA and Logistic Regression.

3.1. Research Steps

Following the process outlined in the journal by Bhattacharjee et al. (2020), the research modeling stages are depicted in Figure 2.

3.1.1. Step 1 Data Acquisition

In the initial stage of data acquisition, the study commenced with gathering historical disruption data from Public Electric Vehicle Charging Stations (PEVCS), supplemented by literature reviews and operational manuals. This phase is designed to establish an understanding of past failures and to uncover any emerging patterns over time (dos Santos & Matias, 2018). This data was then analyzed to evaluate the risk attributes linked to each disruption incident and was conducted alongside the identification of Potential Failure Modes (PFM) by a team of experts (Bhattacharjee et al., 2020).

For this study, focused on PEVCS, the secondary data used included historical disruption records from PEVCSs managed by PLN across Indonesia, obtained through PLN Icon Plus, which manages the information systems at PT PLN (Persero). The dataset spans a six-month period from September 2, 2023 to February 29, 2024.

Over these six months, there were 84,876 disruptions recorded across all PLN-owned PEVCS s in Indonesia. These disruptions were cataloged using the manuals provided by each PEVCS vendor. A significant number of these disruptions are real-time notifications from PEVCSs, resulting in multiple identical incidents occurring on the same day. There were 97 different names of disruptions recorded during this period. The data was further simplified due to occurrences of identical incidents described differently across various PEVCS products, as detailed in Table 3.1 is an example of how disruptions were categorized.

The determination of disruption categorization is derived from the PEVCS vendor manuals and expert assessments based on the disruption names. Not all identified disruption names are categorized due to experts' knowledge limitations and the absence of additional details in the manuals. Commonly, when a disruption occurs, the PLN team notifies the relevant vendor about any physical issues with the unit or contacts PT PLN Icon Plus for IT system or connectivity issues, indicating that not all disruption names are comprehensible to the PLN team. The classification process identified 12 categories of disruptions, detailed as shown on Table 4.

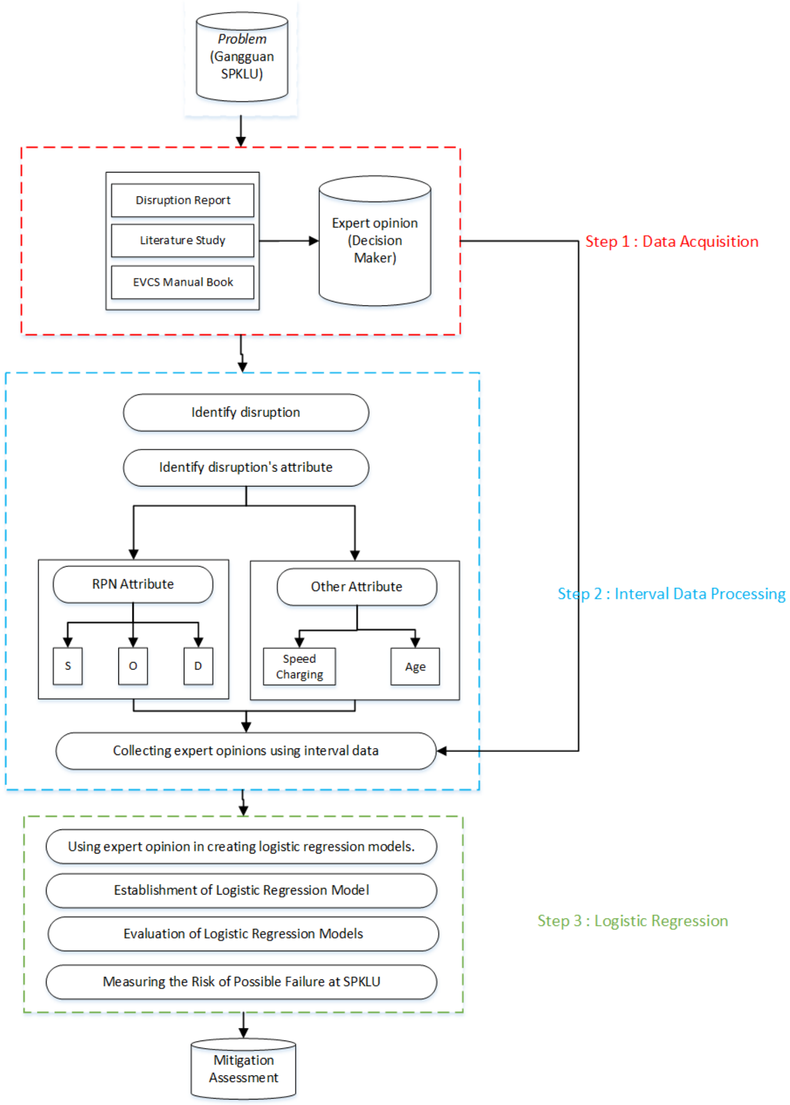

Figure 2. Research process flow

Table 3. Example of Categorizing Disruptions

Disruption Name	Disruption Category	PEVCS Product Name
Emergency stop	Emergency Stop Disruption	DCCT
E-Stop	Emergency Stop Disruption	DCCT / DCWB
EMERGENCY STOP ACTIV	Emergency Stop Disruption	PHG
EMG Fault	Emergency Stop Disruption	PPP
Emergency button is pressed	Emergency Stop Disruption	SIGNET
PE Earth	Grounding Disruption	ACMAX
GroundFailure	Grounding Disruption	DC
AC Ground Fault	Grounding Disruption	PPP
HV GROUND FAULT	Grounding Disruption	PHG
CHAdeMO ground fault detection – warning	Grounding Disruption	PHG

Table 4. Example of Categorizing Disruptions

FM	Disruption Category	Total Events
FM1	Emergency Stop Disruption	25831
FM2	Device Communication Disruption	18158
FM3	Unreplaced Part Disruption	16129
FM4	High Device Temperature Disruption	11159
FM5	Grounding Disruption	4354
FM6	Low Voltage Disruption	2154
FM7	Connectivity Disruption	1107
FM8	Access Door Disruption	1015
FM9	Connector Locking Disruption	486
FM10	High Voltage Disruption	298
FM11	High Current Disruption	82
FM12	Incompatible Charger Disruption	70
	Total	80843

Based on Table 4, 12 categories of disruptions have been identified, categorized by their frequency of occurrence. The Emergency Stop Disruption is the most common, with a total of 25,831 incidents, making it a significant focus for operational risk management. On the other end of the spectrum, the Incompatible Charger Disruption is the least common, occurring only 70 times within a six-month period. Experts will evaluate these disruption categories considering factors such as Severity, Occurrence, Detection, Charging Speed, and Age of the PEVCS in step 2.

3.1.2. Step 2: Interval Data Processing

In step 2, the expert team advances the FMEA procedure by evaluating Severity (S), Occurrence (O), Detection (D), along with extra variables including the charging speed and age of the PEVCS, utilizing interval metrics. This evaluation follows the methodology outlined by Bhattacharjee et al., 2020, where the numerical and categorical assessments of all risk attributes will be incorporated into a logistic regression model. The evaluation scales for each of these variable attributes are structured as shown on Table 5.

Table 5. Rating Scale for Variables S, O, and D

<table>
<tr><td rowspan="2">Severity (S)</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td></tr>
<tr><td colspan="5">No Impact</td><td colspan="5">Hazardous Effect</td></tr>
<tr><td rowspan="2">Occurence (O)</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td></tr>
<tr><td colspan="5">Very Rarely</td><td colspan="5">Very Frequent</td></tr>
<tr><td rowspan="2">Detection (D)</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td></tr>
<tr><td colspan="5">Always detectable</td><td colspan="5">Very Difficult to detect</td></tr>
</table>

According to Salah et al., 2023, the three variables described in the above table 3.3. are as follows: Severity (S) of unit disruptions is rated on a scale of 1-10, where 1 signifies no impact and 10 represents extremely hazardous, taking into account the likelihood and the number of people impacted. Then, Occurrence (O) of these disruptions within a cycle is similarly evaluated on a scale, where 1 indicates the disruption rarely happens and 10 signifies it is very frequent. The detection of these disruptions (Detection, D) is also rated on a scale from 1 to 10, with 1 being easily detectable and 10 being difficult to detect.

Regarding the next variable is PEVCS's charging speed. The scale of charging speed is referred to standards set by Ministry of Energy and Mineral Resources Regulation No. 1 of 2023, Article 1 that said PEVCS speeds are classified as "Slow", "Medium", "Fast", and "Ultra". In this research context, the speed rating is determined by experts based on their observations of where disruptions at PEVCSs most frequently occur. The evaluations, detailed in the table 3.4 below, assign a score of 1 for charging speeds of up to 7 kW, categorized as slow. Medium speed charging, from 7 to 22 kW, scores a 2. Faster charging between 22 to 50 kW scores a 3, and ultra-fast charging over 50 kW scores the highest at 4. These numbers are categorical number not numerical number like variable S, O and D.

Table 6. Rating Scale for PEVCS Charging Speed

PEVCS Charging Speed	Score
<= 7 kW (Slow)	1
7 - 22 kW (Medium)	2
22 - 50 kW (Fast)	3
>= 50 kW (Ultra)	4

Next, concerning the final variable, the Age of PEVCS. Research by (Shi et al., 2022) revealed that consumer behavior influences how long a product remains viable before needing replacement or disposal. In this PEVCS context, the consumers include both the user of PEVCS and PLN which owns the infrastructure. The ages "0-2 years", "2-4 years", and ">4 years" as seen in table 3.5 are the designated life expectancies of PEVCS equipment at PT PLN (Persero). This assessment is grounded in the increased adoption of electric vehicles from 2021 to 2023, which aligned with PLN's significant expansion of PEVCS installations during that period. In this study, the PEVCS age is evaluated by experts based on their observations of the most frequent occurrence of disruptions across different stages of the PEVCS's operational life.

Table 7. Rating Scale for PEVCS Age

PEVCS Age	Score
0 – 2 years	1
2 – 4 years	2
> 4years	3

3.1.3. Step 3: Logistic Regression

In the third step, the objective of employing the FMEA framework with logistic regression is to prioritize Potential Failure Modes (PFM) by their likelihood of causing failures. This step involves developing a logistic regression model using the generalized linear model function. Data preparation is essential prior to logistic regression modeling to ensure the dataset is suitable for predictive modeling. The dataset for this research comprises evaluations made by selected experts from the earlier phase. The format of the dataset that will be processed is as shown Table 8.

Table 8. Dataset table format before statistical analysis is carried out

Expert	Disruption Category	S	O	D	kecepatan	Umur	Failure
expert1	Emergency Stop Disruption	1-10	1-10	1-10	1/2/3/4	1/2/3	0/1
expert1	Device Communication Disruption	1-10	1-10	1-10	1/2/3/4	1/2/3	0/1
expert1	Unreplaced Part Disruption	1-10	1-10	1-10	1/2/3/4	1/2/3	0/1
…	…	...	…	…	..	…	…
Expertx	High Voltage Disruption	1-10	1-10	1-10	1/2/3/4	1/2/3	0/1
Expertx	High Current Disruption	1-10	1-10	1-10	1/2/3/4	1/2/3	0/1
expertx	Incompatible Charger Disruption	1-10	1-10	1-10	1/2/3/4	1/2/3	0/1

In Table 8, the total row count is the product of the 12 disruption categories and the number of selected experts. This dataset, assessed in the second phase, is then incorporated into the logistic regression model using R software (Meurer and Tolles, 2017). The output from this R software simulation will yield the coefficients for each variable. The following is the logistic regression model function to be utilized:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_p X_P$$

where:

- y = Dependent Variable (Failure)
- β_o = Intercept Coefficient
- $\beta_1, \beta_2, \beta_3, \dots, \beta_p$ = koefisien regresi pada variabel independen
- X1, X2, X3, …., Xp = Variabel Independen sebagai prediktor

3.1.4. Model Evaluation

Model diagnostics, including the ROC curve, AUC, and misclassification errors (Gareth et al., 2013; Carter et al., 2016), are performed to evaluate the model's efficacy. The Receiver Operating Characteristic (ROC) curve, Confusion Matrix, and misclassification errors are shown in Figure 3.2. These diagnostics aim to assess the model’s ability to differentiate between conditions of failure and non-failure, and misclassification errors offer insights into the predictive accuracy of the model.

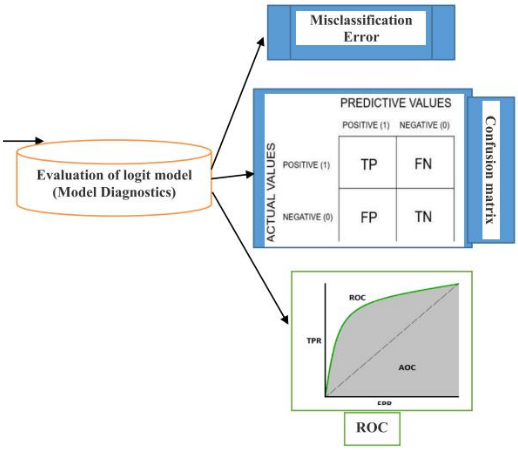

Figure 3. Logit Model Testing

The confusion matrix, also known as the error matrix, is an X by X grid that summarizes the performance of a classification model where x represents the number of classes (Taffese & Leal, 2022). This matrix provides counts of correct and incorrect predictions across various classes, displaying a cross-tabulation of actual versus predicted values. Rows in the matrix represent the actual classes, while the columns indicate the predicted classes. The matrix includes True Positives (TP), which are instances that are actually positive and correctly identified as such; False Positives (FP), which are instances mistakenly identified as positive despite being negative; False Negatives (FN), which refer to positive instances incorrectly labeled as negative; and True Negatives (TN), which are negative instances that are accurately identified.

Misclassification Error assesses the frequency at which the model incorrectly predicts. This is calculated by dividing the number of wrong predictions by the total number of cases:

$$Missclassification\ Error = \frac{FP + FN}{TP\ +\ TN\ +\ FP\ +\ FN}$$

3.1.5. Probability of Failure

Continuing in step 3 and following the evaluation test of the model, the failure probability for each Failure Mode is then calculated using the following Probability Failure (P) formula (Bhattacharjee et al., 2020):

$$e^y = \frac{P}{1-P}$$

Subtitution becomes

$$P^y = \frac{e^y}{1-e^y}$$

From the formula above, P represents the probability of the observed results and y is the linear combination of predictors. The results produced by R in the third step can be used to rank the Failure Modes (PFM) in Table 3.7 based on their failure risk probabilities. FMs with higher failure risk probabilities will be given higher priority in terms of corrective actions. The final outcome of this research will be presented in the Table 9.

On Table 9, disruption categories will be ordered according to the P value, starting with the highest. A disruption qualifies as a Failure if its P value exceeds 0.5 (50%) (Bhattacharjee et al., 2020). When a P value reaches or exceeds

0.5, it is categorized as a "Failure"; otherwise, it is not. By this approach, management can utilize this data to prioritize issues, assess the performance of PEVCS units, and formulate strategies for risk mitigation, including both preventive and corrective measures for each potential failure.

Table 9. Failure status of each disruption

FM	Disruption Category	**P Value**		**Probability**
FM1	Emergency Stop Disruption	(Decimal Number)	(Percentage Number)	Failure / NonFailure
FM2	Device Communication Disruption	(Decimal Number)	(Percentage Number)	Failure / NonFailure
…	……	…..	….	…..
xx	Incompatible Charger Disruption	xxx	xxx	xxxx

4. Result and Discussions

4.1. Result from expert Opinion

In this Research, the experts appointed to assess the disruption categories are employees of PT PLN (Persero) from the Regional Distribution Units (UID) of Greater Jakarta, Banten, and West Java. This decision is based on the fact that the PEVCSs under these units' responsibility have frequently experienced disruptions during the historical period examined. Among the 20 PEVCS locations most prone to disruptions, there were 21,252 recorded disruptions in West Java UID, 10,736 in Greater Jakarta UID, and 5,671 in Banten UID. The determination of who qualifies as an expert from these three UIDs was left to each unit and has been communicated through official internal letters from PLN.

Experts were given an online questionnaire via Google Forms. Assessments were conducted across all 12 disruption categories with evaluations focusing on several variables. The impact measures the extent of the effects caused by the disruptions. Frequency assesses how often these disruptions occur. Detection evaluates how quickly the units can detect these issues. The age of the PEVCS looks at how long the PEVCSs have been installed when the disruptions typically occur. The power speed assesses at what power speed disruptions usually happen. The results from the experts' evaluations are displayed in the Figure 4.

According to Figure 4, each expert independently evaluates each category of disruption. They use a specified scale to assess the various disruptions in terms of Severity (S), Occurrence (O), and Detection (D), recording these as whole numbers on a scale of 1 to 10. Additionally, "Speed" and "Age" are considered categorical variables, each with a rating scale that ranges from 1 to 4. The scales for these variables are detailed in subsection 3.3.2. The findings from these evaluations will subsequently be applied in logistic regression modeling to calculate variable coefficients and estimate the likelihood of failure for each type of disruption.

4.1.1. Result from logistic regression model

In figure 5, the encoding for variables in R takes forms such as "speed2", "speed3", "speed4", "age2", and "age3". R does not display the categories "speed1" and "age1" for each category. This is implemented to prevent multicollinearity, making these two predictor variables serve as dummy variables. For instance, the categorical variable "age" with three categories (1, 2, 3) leads R to establish two dummy variables: one representing category 2 (assigned a value of 1 for category 2, and 0 otherwise), and another for category 3 (assigned a value of 1 for category 3, and 0 otherwise). The first category, "age1", does not require a separate dummy variable as it is represented when both other dummy variables are set to 0.

The regression results depicted suggest that variables S and Age3 have a star (*) in the Pr(>|z|) column, indicating statistical significance at a level less than 0.05, meaning these variables significantly affect the probability of failure. On the other hand, variables S, O, Speed2, Speed3, Speed4, Age2, and Age3, with values over 0.05, do not show enough evidence to be considered significant contributors to the model. Regarding variables S, O, D, which are numeric, and "Speed" and "Age," which are categorical, the encoding in R results in variable names like "speed2", "speed3", "speed4", "age2", etc. R coding does not include "speed1" and "age1" for these categoricals because they act as dummy variables to avoid multicollinearity. As explained, for the categorical "age" with three categories, R creates two dummy variables:

one for category 2 and one for category 3, while the category "age1" is inferred when the other two dummies are both 0.

Figure 4. Dataset table format before statistical analysis is carried out

FM	Disruption Category	Expert1						Expert 2						Expert 3					
		S	O	D	Speed	Age	Failure	S	O	D	Speed	Age	Failure	S	O	D	Speed	Age	Failure
FM1	Emergency Stop Disruption	8	6	9	2	2	1	9	8	3	2	1	0	8	7	2	2	2	0
FM2	Device Communication Disruption	9	4	9	1	2	1	2	2	3	2	3	1	9	8	2	3	2	0
FM3	Unreplaced Part Disruption	9	9	9	3	2	1	8	2	2	2	2	1	7	3	1	3	2	1
FM4	High Device Temperature Disruption	9	2	2	4	2	0	3	2	2	2	3	0	8	8	2	2	3	0
FM5	Grounding Disruption	9	1	2	4	3	0	2	1	1	4	3	0	8	7	2	4	2	0
FM6	Low Voltage Disruption	6	1	8	4	3	0	2	2	1	2	3	0	8	7	2	4	2	0
FM7	Connectivity Disruption	9	9	9	3	1	1	7	5	1	2	2	1	7	6	3	3	2	0
FM8	Access Door Disruption	8	1	4	4	3	0	2	2	1	2	3	0	8	8	2	3	2	0
FM9	Connector Locking Disruption	6	1	6	4	2	0	2	2	1	2	3	0	8	7	2	3	2	1
FM10	High Voltage Disruption	3	1	1	4	3	0	2	2	1	2	3	0	7	9	2	3	1	0
FM11	High Current Disruption	4	2	8	4	3	0	2	2	1	2	3	0	8	7	2	3	2	0
FM12	Incompatible Charger Disruption	2	1	3	4	3	0	2	2	1	2	3	0	7	8	2	2	1	0
FM	Disruption Category	Expert 4						Expert 5						Expert 6					
		S	O	D	Speed	Age	Failure	S	O	D	Speed	Age	Failure	S	O	D	Speed	Age	Failure
FM1	Emergency Stop Disruption	9	8	8	2	1	0	5	6	9	1	2	0	6	2	5	3	1	1
FM2	Device Communication Disruption	9	9	7	3	1	0	10	5	9	3	2	1	6	2	5	3	2	1
FM3	Unreplaced Part Disruption	10	9	8	2	2	1	9	7	8	1	2	1	6	2	6	2	1	1
FM4	High Device Temperature Disruption	8	8	8	2	3	0	6	9	7	2	2	1	7	3	6	3	1	1
FM5	Grounding Disruption	7	7	6	4	1	0	9	5	8	1	2	1	5	1	5	3	1	0
FM6	Low Voltage Disruption	9	2	4	2	2	0	9	3	2	4	2	1	5	1	5	3	1	0
FM7	Connectivity Disruption	9	9	8	3	1	1	9	7	8	1	2	1	5	1	5	2	1	0
FM8	Access Door Disruption	8	7	8	3	2	0	9	1	7	1	2	1	5	1	5	3	1	0
FM9	Connector Locking Disruption	9	6	7	3	3	0	9	2	5	3	2	0	5	1	5	3	1	0
FM10	High Voltage Disruption	7	1	2	3	3	0	9	1	6	3	2	0	5	2	5	3	2	0
FM11	High Current Disruption	9	6	7	2	3	0	9	1	6	1	2	0	5	2	5	2	2	1
FM12	Incompatible Charger Disruption	8	4	5	2	2	0	9	5	2	2	2	0	5	1	5	2	2	0
FM	Disruption Category	Expert 7						Expert 8						Expert 9					
		S	O	D	Speed	Age	Failure	S	O	D	Speed	Age	Failure	S	O	D	Speed	Age	Failure
FM1	Emergency Stop Disruption	8	4	6	4	1	1	3	3	4	4	1	0	9	3	1	4	2	1
FM2	Device Communication Disruption	10	5	7	2	1	1	2	3	6	2	1	1	9	3	1	4	3	1
FM3	Unreplaced Part Disruption	10	7	6	2	1	1	2	3	3	1	1	0	9	3	1	4	1	1
FM4	High Device Temperature Disruption	8	6	4	4	1	1	9	1	9	1	3	0	9	3	3	4	3	1
FM5	Grounding Disruption	10	3	6	4	1	1	2	2	2	1	3	0	9	3	3	4	1	1
FM6	Low Voltage Disruption	8	5	6	2	1	1	2	4	6	1	2	0	9	3	2	4	1	1
FM7	Connectivity Disruption	8	5	5	2	1	1	2	3	4	1	1	0	9	5	3	4	1	1
FM8	Access Door Disruption	9	6	5	4	1	1	2	2	2	1	3	0	9	3	3	4	1	1
FM9	Connector Locking Disruption	8	4	6	2	1	1	2	2	2	1	2	0	9	3	2	4	1	1
FM10	High Voltage Disruption	7	2	2	2	1	1	2	2	2	1	1	0	9	2	2	4	1	0
FM11	High Current Disruption	5	5	4	2	1	0	2	2	2	1	2	0	9	2	2	4	1	0
FM12	Incompatible Charger Disruption	5	2	2	2	1	0	2	3	2	1	2	0	9	3	3	4	1	1

Where:

Failure	=	Failure Occurs (1 if occurs 0 if not)	Value 3 in "Speed"	=	22 - 50 kW (Fast)
S	=	Severity	Value 4 in "Speed"	=	>= 50 kW (Ultra)
O	=	Occurrence	Value 1 in "Age"	=	0 – 2 years
D	=	Detection	Value 2 in "Age"	=	2 – 4 years
Value 1 in "Speed"	=	<= 7 kW (Slow)	Value 3 in "Age"	=	> 4years
Value 2 in "Speed"	=	7 - 22 kW (Medium)			

```
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -3.0348     1.3177  -2.303   0.0213 *
S               0.3394     0.1389   2.443   0.0146 *
O              -0.0239     0.1072  -0.223   0.8236
D               0.1358     0.1214   1.118   0.2635
Speed2          0.3376     0.9177   0.368   0.7130
Speed3         -0.1629     0.8971  -0.182   0.8559
Speed4          0.3193     1.0264   0.311   0.7557
Age2           -0.2553     0.5747  -0.444   0.6569
Age3           -1.8935     0.9079  -2.085   0.0370 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)
```

Figure 5. Logistic regression results using R software

From logistic regression result in figure 4.1, maka the logistic regression formula can be written as follows:

$$y = -3.0348 + (0.3394 \times \mathrm{S}) + (-0.0239 \times \mathrm{O}) + (0.1358 \times \mathrm{D}) + (-0.3376 \times \mathrm{speed2}) + (-0.1629 \times \mathrm{speed3}) + (0.3193 \times \mathrm{speed4}) + (-0{,}2553 \times \mathrm{age2}) + (-1.8935 \times \mathrm{age3})$$

where:

y	=	Failure	speed3	=	22 - 50 kW (Fast)
S	=	Severity	speed4	=	>= 50 kW (Ultra)
O	=	Occurrence	age2	=	2 – 4 years
D	=	Detection	age3	=	> 4years
speed2	=	7 - 22 kW (Medium)			

4.1.2. Model Evaluation

a. Receiver Operating Characteristic - Area Under the Curve (ROC – AUC)

Generally, the Area Under the Curve (AUC) on the Receiver Operating Characteristic (ROC) curve varies from 0 to 1, and a higher AUC value signifies greater accuracy in differentiating positive from negative results. In this research, the model achieved an AUC of 0.875, suggesting it is highly effective in predicting and distinguishing among various categories, as depicted in Figure 4.2. This demonstrates the model's reliability in accurately analyzing and classifying data.

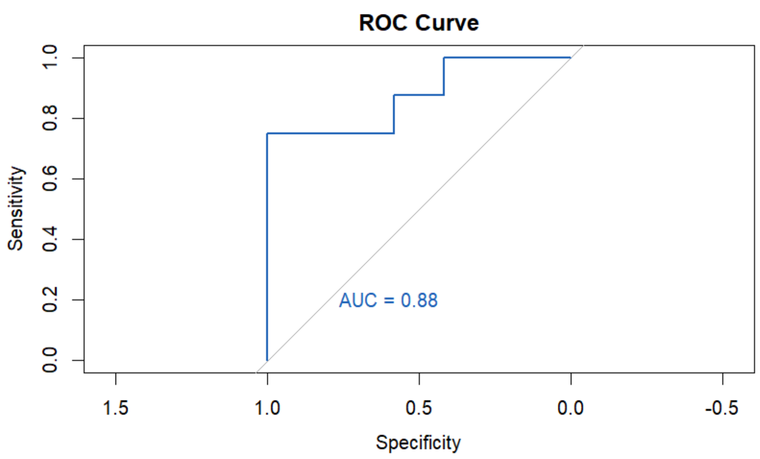

Figure 6. ROC AUC curve

b. Confusion Matrix

A Confusion Matrix is a table that depicts the performance of a classification model on a dataset where the actual values are established. It categorizes predictions into four segments: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). These segments are indicative of the model's accuracy in applying the correct categories to the analyzed data. In this study, the outcomes of the model evaluation using the confusion matrix are displayed in Figure 7, described as follows:

```
          Reference
Prediction  0  1
         0 11  2
         1  1  6
```

Figure 7. Confusion Matrix Evaluation Result

The model's performance in predicting failures and non-failures can be evaluated through its results across various scenarios. It successfully identified True Positive (TP) outcomes six times, accurately recognizing each incident where a failure was supposed to be detected. Additionally, it correctly identified True Negatives (TN) on eleven occasions, effectively indicating the absence of failure in those cases. However, the model was not without errors; it incorrectly predicted non-failure twice when failures actually occurred, known as False Positives (FP). Moreover, there was one instance of a False Negative (FN), where the model indicated a failure, but none had actually taken place.

c. Missclassification Error

The misclassification error which indicates how frequently a model misclassifies instances is calculated as the ratio of incorrect predictions to the total number of predictions made. According to the assessment, the model exhibits a misclassification error rate of 15%, which means that 15% of the model's predictions on the test data were incorrect. This error rate is computed using the formula FP+FN/(TP+TN+FP+FN), derived from the previous confusion matrix. However, it is notable that the model correctly classified 85% of the cases.

4.1.3. Probability of Failure

The logistic regression analysis provides coefficients for each predictive variable After inserting all the regression coefficients and determining the value of y, which leads to the calculation of P, the results are as follows:

Table 10. Failure status of each disruption

FM	Kategori Gangguan	P Value		Probability
FM1	Emergency Stop Disruption	0,59779	59,8%	Failure
FM2	Device Communication Disruption	0,55250	55,2%	Failure
FM3	Unreplaced Part Disruption	0,52931	52,9%	Failure
FM4	High Device Temperature Disruption	0,48254	48,3%	NonFailure
FM5	Grounding Disruption	0,46460	46,5%	NonFailure
FM6	Low Voltage Disruption	0,43539	43,5%	NonFailure
FM7	Connectivity Disruption	0,43059	43,1%	NonFailure
FM8	Access Door Disruption	0,40310	40,3%	NonFailure
FM9	Connector Locking Disruption	0,37128	37,1%	NonFailure
FM10	High Voltage Disruption	0,34844	34,8%	NonFailure
FM11	High Current Disruption	0,34665	34,7%	NonFailure
FM12	Incompatible Charger Disruption	0,30021	30,0%	NonFailure

In Table 10, data on the potential for failure within each PEVCS disruption category is shown. Analysis of the P values reveals that the "Connector Locking Disruption" and "Access Door Disruption" have probabilities of 34.7% and 30%, indicating a low likelihood of these disruptions causing failures in the PEVCS units. On the other hand, "Device Communication Disruption", "Connectivity Disruption", and "Emergency Stop Disruption" show higher probabilities of approximately 59.8%, 55.2%, and 52.9%, and are thus classified as nonfailures. According to (Bhattacharjee et al., 2020)a disruption is deemed a failure if it possesses a P value exceeding 0.5 (50%).

4.2. Discussion

Logistic regression analysis using R software indicated that the severity of disturbances (Severity), with a coefficient of 0.3394, significantly increases the risk of failure at Public Electric Vehicle Charging Stations (PEVCS). This emphasizes the need to identify and reduce high-severity disturbances to enhance system reliability. To understand the influence of significant variables on failures, additional simulations were performed under two scenarios: "Actual" and "Extreme," as outlined on Table 11.

Table 11. Simulation results for actual and extreme conditions

	a	b	c	d	Actual		Extreme
indep var, X	coeff	min	mean	max	a*c		a*d
S	0,33940	2	6,98	10,00	2,37		3,39400
O	-0,02390	1	4,29	9,00	-0,10247125	-	0,21510
D	0,13580	1	4,68	9,00	0,63		1,22220

In Table 11, the coefficient values are derived from prior regression results, while the "min," "mean," and "max" values are based on expert opinions. The actual scenario uses the mean value for the coefficient multiplication, whereas the extreme scenario uses the maximum value for the coefficient multiplication. Under these two scenarios, the significant variables identified are Severity and Age3, as shown on Figure 8.

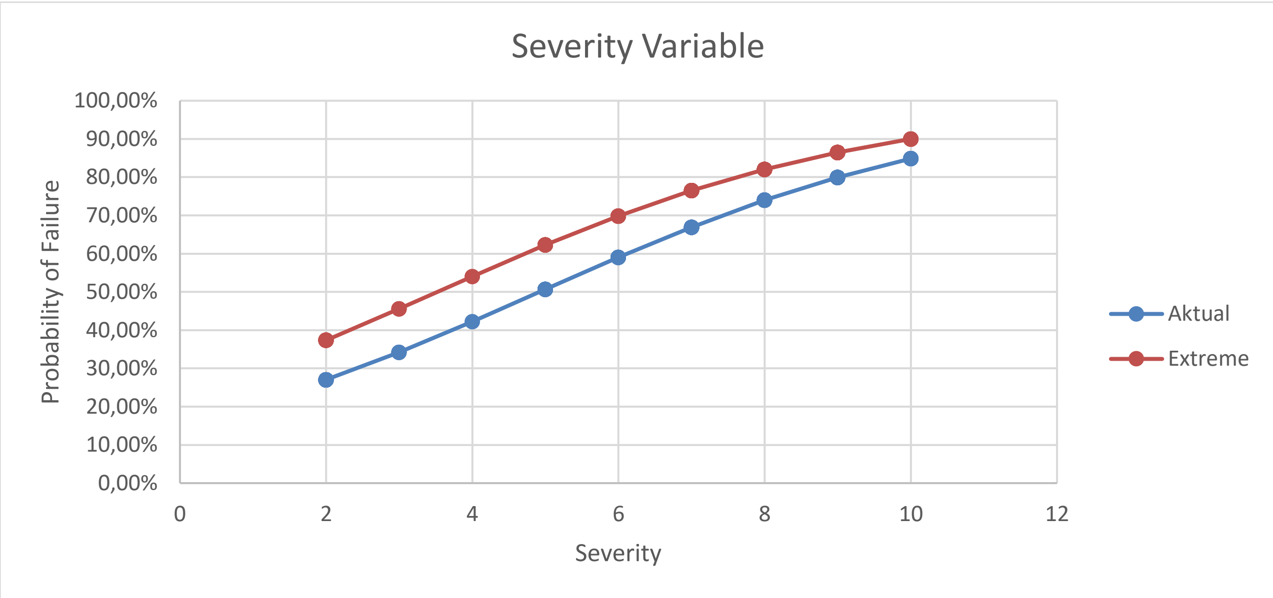

Figure 8. Graph showing the effect of the Severity variable on failures

Figure 8 illustrates that using the maximum values from Table 4.3 under Extreme conditions does not significantly increase the failure probability at lower values. For instance, at a Severity value of 2, the extreme condition results in a failure probability of around 40% (higher than the actual condition). The graph shows both curves following a linear trend, increasing gradually up to nearly 90%. This suggests a strong positive correlation between higher 'Severity' levels and increased 'Probability of Failure'. Additionally, the age of PEVCSs is categorized into three types: age1 (less than 2 years), age2 (2-4 years), and age3 (more than 4 years). Previous regression results in Figure 4.1 identified age3 as a significant variable influencing failure. A simulation was then conducted on the second significant variable, "age3," with the shown Figure 9.

Figure 9 illustrates that the failure probability increases with the aging of PEVCSs. In the actual scenario, the failure probability for the age1 category is already at 66%, with a significant increase in the age3 category, reaching around 93%. This aligns with regression results indicating that the age3 variable significantly affects failures. Under extreme conditions, using the same data from Table 4.4, the probabilities for all age categories (age1, age2, and age3) are above 90%, with age3 reaching 98% under extreme conditions. This highlights the substantial impact of PEVCS age on its failure probability. Regarding charging speed, ultra-fast charging (>= 50 kW) with a coefficient of 0.3193 significantly increases the risk of failure, indicating that high-speed charging systems need careful design to prevent overload. In contrast, low to medium charging speeds (7-22 kW and 22-50 kW) with coefficients of -0.3376 and -0.1629, respectively, reduce failure probability, suggesting that optimizing PEVCS operational parameters for these speeds can lower risk.

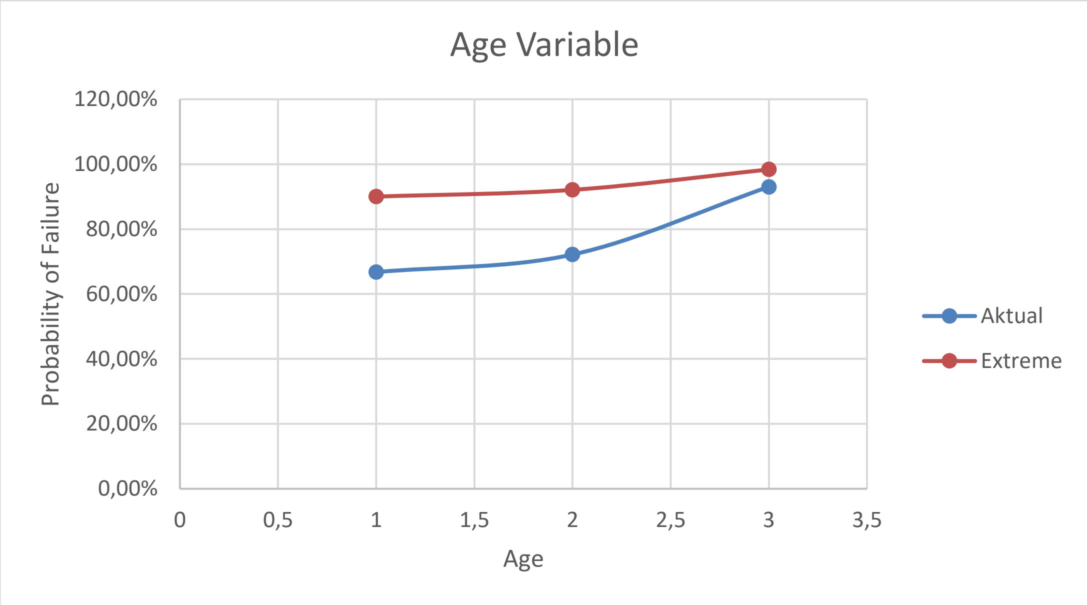

Figure 9. Graph showing the effect of the Age variable on failures

5. Conclusions

This research is designed to quantify the potential for failures that render PEVCS units Unavailable, allowing for the prioritization of issues that lead to such failures and the minimization of damage risks within PEVCSs. The results identify 12 disruption categories within PLN's PEVCSs, with three of these disruptions exhibiting a failure probability exceeding 50%. Regression results demonstrate that independent variables like Severity and Age3 (PEVCS age over 4 years) significantly influence failure as the dependent variable. Preventive and corrective measures are recommended for these three critical disruptions based on guidance from manuals and experts, positioning them as the primary focus for management to resolve these disruption issues.

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