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FMEA-Based Logistic Regression Model for the Evaluation of Photovoltaic Power Plant Risk

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Abstract

The purpose of this research is to identify the primary operational risks associated with photovoltaic power plants and develop effective risk management strategies to optimize the operation of existing plants and mitigate risks for future plants that will be constructed as part of the new renewable energy (EBT) transition agenda until 2030. The integration of Failure Mode and Effect Method Analysis (FMEA) with logistic regression provides the formation of a risk treatment ranking that management should prioritize. Risk assessment relies on the expertise and experience of professionals in performing their responsibilities associated with photovoltaic power plants. The research findings have identified 10 potential risks associated with improving photovoltaic power plants operations to prevent failure or damage to the system. These risks are categorized into five stages of the operation process: planning and procurement, installation, operation, and maintenance. Risk rankings and mitigation are generated to prioritize actions aimed at limiting the occurrence of failure/damage and low-capacity factors in photovoltaic power plants as recommendations for the management.

Keywords: FMEA, Photovoltaic Power Plant, Renewable Energy, Risk.

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1. Introduction

Global warming gives rise to various sustainability issues, one of which is climate change. This risk creates a sense of urgency for all stakeholders to actively reduce the negative consequences that ensue and promote sustainable development. An approach to mitigate the adverse effects of global warming involves decreasing greenhouse gas emissions through the promotion of renewable energy sources and the reduction of fossil fuel consumption.

Based on the data from RUPTL 2021-2030 (2021), the Indonesian electricity utility company aims to construct power plants with a total capacity of 40,575 megawatts by 2030. Out of this, 20,923 megawatts, or 51.6% of the total capacity, will be generated from renewable energy sources. The remaining 19,652 megawatts (48.4%) of the total capacity, will be generated from fossil fuels. Out of the proposed EBT generator development, a total of 4,680 MW will be generated specifically from solar power, which is often referred to as a photovoltaic (PV) power plant. This indicates that PV power plant is the second most prominent generator in the renewable energy mix that will be constructed by 2030 (RUPTL 2021-2030., 2021). According to data obtained from the Renewable Energy and Energy Conservation statistics book (Sekretaris DirJen EBTKE, 2016), the cost of constructing a photovoltaic (PV) power plant is substantial, amounting to 995 USD/KW. Investment calculations for PV power plants, following EBTKE recommendations, consider a capacity factor (CF) of 17% and a plant lifespan of 25 years. The capacity factor (CF) is the ratio of the actual electrical energy production in a given period (kWh) to the maximum electricity production possible in that period (Mensah et al., 2019). The power plant lifespan refers to the specified number of years used in calculating the investment for the power plant, assuming that it will operate effectively throughout that period. The predicted lifespan of the power plant and the CF value of the PV power plant are crucial factors for accurately determining investment returns in PV power plant development. PV power plant that deviates from calculated criteria can potentially result in investment losses.

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According to data from Indonesian electricity company until December 2023, there are currently 290 PV power plants under management. Out of the total PV powerplant, 28 PV powerplant experienced permanent damage and temporary damage below the standard life of the PV powerplant.

Based on historical statistics, it is clear that a certain proportion of PV power plants have experienced damage before reaching their intended lifespan. More precisely, 3% of individuals have encountered permanent damage, whereas 7% have had temporary damage. Alongside the consideration of how long the power plant has been in operation, the capacity factor (CF) of the PV power plant is also considered, with a minimum need of 17% to meet the calculations for EBTKE investments. Historical data from December 2023 shows that 94% of the total PV power plants have a Capacity Factor (CF) percentage that is less than 17%, while the remaining 6% have a CF number that exceeds 17%.

This research aims to identify the primary risk that led to the premature expiration of photovoltaic power plants within 25 years and result in a capacity factor (CF) below 17%. Additionally, it seeks to determine the necessary measures to optimise the operations of solar power plants and mitigate these risks. The objective of this research is to identify effective risk management strategies to optimize the operation of existing PV Power Plants and to develop mitigation measures for PV Power Plants that will be constructed as part of the new renewable energy transition agenda until 2030.

The paper is structured as follows: the second section provides a literature review of pevious study related to risk in PV power plant. The third section of the document focuses on the research methods, specifically discussing the fundamental concepts of FMEA, logistic regression, and case study. The case study also encompasses the suggested logistic regression method. This method is demonstrated using a numerical example to analyze the failure of PV power plant located in Indonesia. The specific results of the proposed investigation are discussed in the fourth section. Lastly, the final section encompasses the closing portion of the report, as well as the limits of the current work and the potential for future research.

2. Literature Review

ISO 31000:2018 defines risk as effect of uncertainty on objectives. Operational risk refers to the uncertainty or potential loss that a firm may encounter while conducting its day-to-day business operations. The four causes of operational risk are internal process, system failure, external events, and people. The purpose of operational risk analysis is to facilitate firms in implementing effective risk mitigation strategies and minimizing any adverse effects that may impede the achievement of the company's objectives. ISO 31010:2016 regulates the methodologies employed in risk assessment. Risk assessment is a fundamental part of risk management. It entails a methodical approach to identifying the possible effects on objectives, estimating the likelihood and consequences of occurrence, and making well-informed judgments about future measures to mitigate or control the risk. The risk assessment method comprises three stages: risk identification, risk analysis, and risk evaluation. FMEA (Failure Mode and Effect Analysis) is one of the 31 risk analysis techniques contained in ISO 31010:2016.

When utilizing PV power plant to fulfill energy requirements, it is important to take into account the various risks associated with it (Shojaeimehr & Rahmani, 2022). The study performed by Horváth & Szabó (2018) identifies five key activities of a community scale PV powerplant business. These activities include customer management, program management (which encompasses consumer protection, data reporting, and compliance), installation, procurement, and operations and maintenance. In their study, Shojaeimehr and Rahmani (2022) conducted a comprehensive analysis of risk management by categorizing various risk areas such as economic, technical, institutional, environmental, and social. They identified a total of 54 risks, including high investment values, fluctuations in interest rates and inflation, financial risks, natural disasters, radiation fluctuations, environmental risks, social risks such as war, terrorist acts, and political instability, component risks such as panel damage and changes in technology, as well as challenges in finding employees in remote areas and specific labor requirements. Ardian Burhandono & Sinaga (2022) conducted research on PV powerplant failure, categorizing failures into four types: inverter damage, PV module damage (external and internal), environmental factor damage (human error and environmental factors), and electrical factors.

Assessment of the potential risks associated with solar power facilities in Kerala A study conducted by Mohamed et al. (2019), in India focused on investigating the status of solar power projects in Kerala. The objective of this research was to establish a comprehensive understanding of the various risk factors involved and the corresponding control measures. A number of surveys were carried out on numerous parties involved in the installation and operation of solar power plants to identify many risk variables and their corresponding sub-factors. Mohamed et al., 2019 employed the Analytic Hierarchy Process (AHP) method to identify and quantify elements utilizing a decision-making tool. There are a total of 5 major technical risks displayed in the table 1.

Table 1. Major Technical Risk

No	Risk
1.	The availability of skilled technicians is very limited.
2.	Feasibility of land for solar energy project is very less
3.	Weather fluctuations have a deleterious impact on solar energy projects.
4.	Periodic maintenance schedule and maintenance cost is very high
5.	Availability of technicians after installation is very less

Source: (Mohamed et al., 2019)

Meanwhile, the technical risk findings identified by Shojaeimehr & Rahmani (2022) from the results of research conducted in Iran, by utilizing literature reviews and expert interviews to identify risks resulted in 15 technical risks which are sorted as shown in table

Table 2. PV power plant technical risk

No	Risk
1.	Applicability in areas with certain climatic conditions
2.	Does not generate electricity at night
3.	Panel fragility
4.	Difficult to find workers in remote areas
5.	Requires special workforce
6.	Equipment damage in transportation
7.	Decreased performance due to dirt on the panel
8.	Inaccessibility of new technology
9.	Equipment failure
10.	Human error
11.	Technology changes
12.	Solar variability
13.	Very high air temperature
14.	Low efficiency of the technology used
15.	Failure to connect to the power grid

Source:(Shojaeimehr & Rahmani, 2022)

Pimpalkar et al. (2023) did an extensive examination of failure scenarios and the impact analysis of solar photovoltaic systems utilizing the FMEA methodology. The research findings indicate that enhancing the dependability of solar PV systems necessitates more effective maintenance scheduling and potential enhancements in design.

3. Methods

This research employed the FMEA (Failure Mode and Effect Analysis) research method, which is a systematic approach for identifying potential failures by assessing the risks that contribute to failure (Liu et al., 2013; Stamatis, 2003). This method has proven effective in diverse industries such as manufacturing, power generation, and automotive (Bhattacharjee et al., 2020). This research was conducted in three stages, as shown in Figure 1.

The problem formulation is established during the initial stage of the research. Subsequently, risk identification is conducted by examining literature studies, supporting papers, and expert opinions. An extensive literature review was conducted on prior research pertaining to PV power plant risk analysis and the employed research methodologies. The initial step generates a compilation of failure modes that result in failure in PV powerplant.

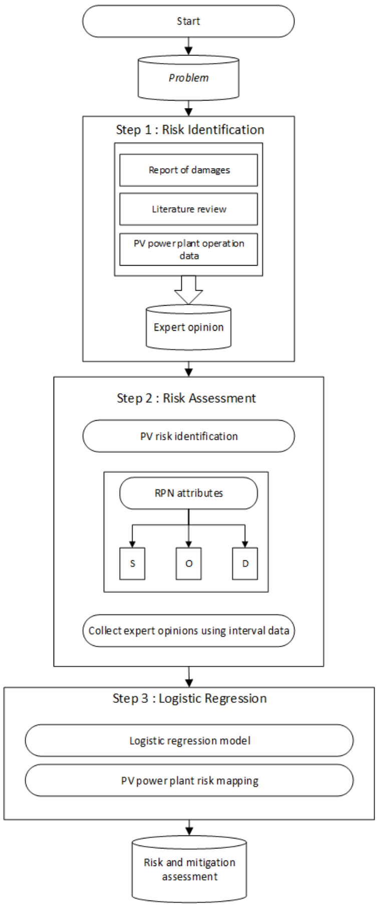

Figure 1. Research flow diagram

Table 3. Rating Failure modes

Rank	Severity (S)	Occurrence (O)	Detection (D)
10	Hazardous	Extremely high	Absolute uncertainty
9	Serious	Very high	Very remote
8	Extreme	Repeated failures	Remote
7	Major	High	Very low
6	Significant	Moderately high	Low
5	Moderate	Moderate	Moderate
4	Low	Relatively low	Moderately high
3	Minor	Low	High
2	Very minor	Remote	Very high
1	None	Nearly impossible	Almost certain

The second phase of this study involved conducting a risk assessment. The assessment focused on a list of failure modes identified in the previous phase. Experts assigned scale values to assess the Severity (S), Occurrence (O), and Detection (D) attributes for each failure mode. The scale utilized corresponds to the scale employed in the previous study done by Liu et al. (2013), as presented in table 3. The evaluation of risks associated with failure modes is conducted using the risk analysis methodology employed in this study, namely the Failure Mode and Effect Analysis (FMEA) approach. The current output consists of severity, occurrence, and detection scale data for each risk, which are subsequently utilized to ascertain risk priority.

The third stage involves defining risk priorities by employing the logistic regression method to ascertain the weighting of S, O and D variables in terms of their impact on failure. The integration of FMEA with the logistic regression method, as researched by Bhattacharjee et al. (2020), seeks to mitigate the limitations of traditional FMEA approaches. The regression model will generate the likelihood of failure for each failure mode. The last action undertaken is to determine risk mitigation measures that can be implemented to address the identified risk priorities, which are determined by risk rating. These measures then serve as input and suggestions for management.

This study integrates two methodologies, namely Failure Mode and Effects Analysis (FMEA) and logistic regression, following the approach employed in a previous study conducted by Bhattacharjee et al., 2020. The aim is to identify the most critical risks by replacing the limitations associated with the standard calculation of Risk Priority Numbers (RPN) in FMEA. Traditional RPN computations may result in the repetition of numbers due to the multiplication of severity, occurrence, and detection factors. This can lead to identical numerical values with varying implications (Shebl et al., 2012). Traditional FMEA assigns equal importance to the three risk attributes, but in reality, S, O, and D may have varying degrees of significance (Bhattacharjee et al., 2020). The original Failure Mode and Effects Analysis (FMEA) technique faced various limitations in its practical implementation. These drawbacks include the reliance on severity (S), occurrence (O), and detection (D) levels to calculate the Risk Priority Number (RPN), the assumption of equal relevance for each risk factor, the subjective nature of member opinions, and the method used to integrate the risk factors. According to Gargama & Chaturvedi (2015), inappropriate risks that lead to the same failure rating can have varying implications for risk. Conventional FMEA-based RPN calculations lack sufficient strength in prioritizing failure modes. The relative magnitudes of the three components (S, O, and D) were not taken into account. Various permutations of S, O, and D can yield identical RPN values, thus accurately estimating these three variables is challenging (Liu et al., 2013). The regression method is utilized to ascertain the sequence of failure probabilities, which serves as a guideline for management to implement corrective measures. Figure 2 displays the framework that used in this research.

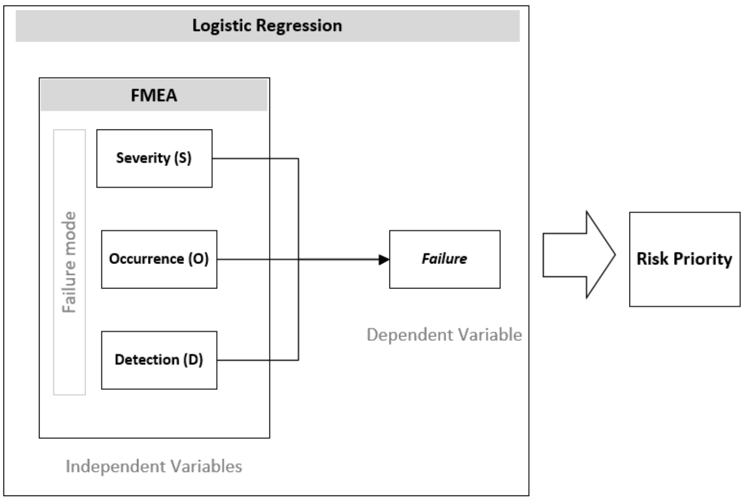

Figure 2. Methodology framework

The attributes severity (S), occurrence (O), and detection (D) are considered independent variebles, whereas failure is considered the dependent variable. These variables are aspects of the standard FMEA approach. Logistic regression is employed to create a mathematical model that ranks failure modes/risks requiring attention as an alternative to traditional risk priority number (RPN) computations.

The outcomes of the S O D evaluation conducted using the Failure Mode and Effects Analysis (FMEA) technique were combined with a logistic regression model constructed using a generalized linear model function. This model use the equation to calculate the probability of damage risk. The Potential Failure Modes (PFM) are organized based on the potential risk of damage. Therefore, the model will assist managers in suggesting appropriate measures to address the issue. The logistic regression model employed is as follows.

$$y = \beta_0 + \beta_1 S + \beta_2 O + \beta_3 D \quad (1)$$

Where y is the risk of failure, β0, β1, β2, βn are regression beta coefficients, S, O, D are the dependent variables.

Once the logistic regression equation was obtained, a model fit analysis was conducted using the confusion matrix and Receiver Operator Characteristic (ROC).

The confusion matrix, also known as a classification matrix, is a statistical tool used by statisticians in logistic regression to assess appropriateness (Hilbe, 2009). The confusion matrix consists of four components: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). TP refers to cases where both the actual data and the model's prediction are positive. TN refers to cases where both the actual data and the model's prediction are negative. FP refers to cases where the actual data is negative, but the model predicts a positive value. FN refers to cases where the actual data is positive, but the model predicts a negative value. The mapping of these four components can be represented in table 4.

Table 4. Confussion matrix

		Prediction	
		Positive	Negative
Actual	Positive	**TP**	**FN**
	Negative	**FP**	**TN**

The misclassification error can be determined based on the data provided in the confusion matrix table. This computation is used to determine the accuracy of the regression model's predictions. A model is considered better when it has a smaller misclassification error value (Bhattacharjee et al. in 2020). The formula for calculating misclassification error is as follows:

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

The ROC curve, also known as the receiver operator characteristic, is commonly employed by statisticians to classify cases using logistic models (Hilbe, 2009). The ROC curve is a graphical representation of the probability of correctly classifying a binary outcome. The Area Under Curve (AUC) is a quantitative measure of how well the model can distinguish between the two classes. The Receiver Operating Characteristic (ROC) curve is constructed using sensitivity, also known as the true positive rate (TPR), as the vertical axis (Y-axis), and specificity, also known as the false positive rate (FPR), as the horizontal axis (X-axis). Both quantities are derived using the subsequent mathematical equation:

$$\text{TPR} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

$$\text{FPR} = \frac{\text{FP}}{\text{FP} + \text{TN}} \quad (4)$$

4. Result and Discussions

The list of potential failure mode is carried out by identifying the risks that may occur on PV power plant by conducting a literature study to obtain a conceptual framework against the risk of damage of PV powerplant to be developed through discussion with experts based on the practical PV power plant business processes. Identification of potential failure is related to the problem statement and objectives of the research discussed with experts based on literature studies and historical data on damage that occurred. Framework of potential failure modes in this study is depict in figure 3.

The scale assessment is conducted by utilizing a Decision Maker (DM), who is an expert in the industry and possesses ample knowledge. The assessment is performed by evaluating linguistic variables using scale numbers. The Severity (S), Occurance (O) and Detection (D) rating scale ranging from 1-10 according to the study conducted by Liu (2013) is shown in Table 6.

Risks are evaluated at four stages of the process: (1) Planning and procurement, (2) Installation, (3) Operation, and (4) Overhaul/maintenance. The process of identifying the four steps yields a list of failure modes, or potential risks, which are then gained through expert discussions. It is possible to conclude that the risks that have been discovered are those that are mentioned in Table 5.

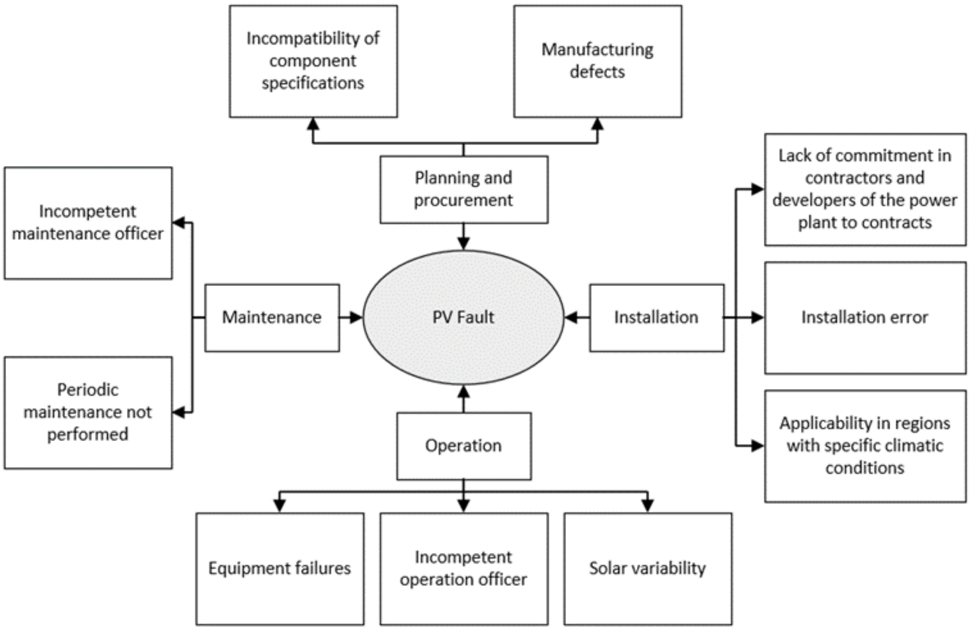

Figure 3. Potential failure mode

Table 5. List of identified Failure modes

Process	Code	Failure mode	Source
Planning and procurement	FM1	Incompatibility of component specifications	(Ioannou et al., 2017) (Shojaeimehr & Rahmani, 2022)
	FM2	Manufacturing defect	(Ardian Burhandono & Sinaga, 2022)
Installation	FM3	Lack of contractor commitment	(Shojaeimehr & Rahmani, 2022)
	FM4	Incorrect installation/ installation error	(Ardian Burhandono & Sinaga, 2022) (Ioannou et al., 2017)
	FM5	Applicability in regions with specific climatic conditions	(Ardian Burhandono & Sinaga, 2022) (Gaurav et al., 2011) (Mohamed et al., 2019)(Shojaeimehr & Rahmani, 2022)
Operation	FM6	Equipment failures	(Ardian Burhandono & Sinaga, 2022) (Akram et al., 2022) (Herz et al., 2023)(Li et al., 2023)(Shojaeimehr & Rahmani, 2022)
	FM7	Incompetent operation officer	(Horváth & Szabó, 2018) (Gaurav et al., 2011) (Mohamed et al., 2019) (Shojaeimehr & Rahmani, 2022)
	FM8	The installation site is devoid of solar	(Shojaeimehr & Rahmani, 2022)

Process	Code	Failure mode	Source
		irradiation/ Solar variabbility	
Maintenance	FM9	Incompetent maintenance officer	(Horváth & Szabó, 2018) (Gaurav et al., 2011) (Mohamed et al., 2019)(Shojaeimehr & Rahmani, 2022)
	FM10	Periodic maintenance not performed.	(Kumar et al., 2023)

The scale assessment is conducted by utilizing a Decision Maker (DM), who is an expert in the industry and possesses ample knowledge. The Severity (S), Occurance (O) and Detection (D) rating scale ranging from 1-10. Risks are evaluated at four stages of the process: (1) Planning and procurement, (2) Installation, (3) Operation, and (4) maintenance. The process of identifying the four steps yields a list of failure modes, or potential risks, which are then gained through expert discussions. It is possible to conclude that the risks that have been discovered are those that are mentioned in Table 4.

An assessment of the risk/failure modes that have previously been identified is carried out. The assessment was carried out using a questionnaire by assessing severity (S), occurrence (O) and detection (D). Expert assessment produced the following results in Table 5. The assessments given by the eight experts were assessed based on criteria on a scale of 1 to 10 which reflected severity, occurrence and detection. The assessment is based on the skills and experience of experts in carrying out their duties related to PV power plant. The severity value given, the greater the number assessed, the greater the impact of the risk on the organization. Occurrence criteria indicate the possibility of a risk occurring, the higher the number given, the greater the probability or frequency of the risk occurring. Meanwhile, detection shows the level of ease in detecting a risk event, the higher the number given, the easier it is for a risk to be detected. Organizations that have good risk governance tend to be able to easily detect risks and implement controls or mitigation to overcome these risks.

Table 5. Assessment failure by expert

Failure Mode	Severity								Occurrence								Detection							
	A1	A2	A3	A4	A5	A6	A7	A8	A1	A2	A3	A4	A5	A6	A7	A8	A1	A2	A3	A4	A5	A6	A7	A8
FM1	10	9	7	10	2	9	4	9	10	7	7	4	2	7	3	7	1	4	4	3	2	8	2	8
FM2	10	5	7	10	3	8	8	10	10	7	6	4	3	8	7	7	4	1	4	2	2	7	4	6
FM3	10	9	7	10	2	9	10	9	5	7	7	5	3	9	3	5	5	4	3	3	2	9	5	7
FM4	10	3	7	10	1	9	9	10	5	3	7	3	2	9	5	8	5	2	4	3	1	9	5	8
FM5	10	8	7	10	3	9	7	7	5	8	5	2	2	9	4	5	5	7	3	2	1	9	7	9
FM6	10	6	7	9	2	9	6	8	5	6	6	5	2	9	5	6	5	6	3	3	1	9	4	5
FM7	10	8	7	10	4	9	6	9	10	8	7	5	2	9	4	7	3	7	3	3	1	9	5	7
FM8	10	5	8	9	3	9	7	6	5	5	4	5	2	9	5	5	5	5	3	3	2	9	4	7
FM9	10	6	7	9	3	9	8	7	5	6	7	3	3	9	6	7	5	6	4	2	1	9	5	7
FM10	10	7	7	9	3	9	7	8	5	7	8	3	3	9	6	9	5	7	5	2	1	9	6	6

4.1. Logistic Regression Model Result

Based on the assessment of 3 criteria that have been carried out by experts, the data collected is processed using the R studio application to obtain the desired logistic regression model for calculating the probability of default as a substitute for conventional RPN calculations, resulting in the following regression model:

$$y = -0.54794 + 0.03708\, S + 0.57525\, O - 0.32425\, D \tag{3}$$

where y is the dependent variable (failure) and S, O, D are independent variables.

Table 6 shows the values in the model formed. The first column contains the beta coefficient of the intercept and also the coefficients of other independent variables. The significance of the variable is assessed from the p value shown in the Pr(> |z|) value in the table. (1- The Pr value (> | z |) shows that the parameter is significant to the model, namely with a lower Pr value (> | z |) the higher statistical significance is obtained. Table 6 shows that there is 1 variable that significantly influence the dependent variables, which is Occurrence (O) variables with Pr(> |z|) values of 0.0202, which means the confidence level for these variables is >95%. It is known from the model that the severity variable has a lower confidence level compared to the other two variables.

Table 6. Coefficients Table

Explanatory variable	Coefficients estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-0.54794	1.08331	-0.506	0.613
S	0.03708	0.1454	0.255	0.7987
O	0.57525	0.24775	2.322	0.0202*
D	-0.32425	0.213	-1.522	0.1279

The coefficient of the S variable is 0.03708, indicating that for every increase in the S variable, the log odds of the dependent variable increase by 0.03708. However, the high Pr(> |z|) value of 0.7987 suggests that the S variable does not have a statistically significant relationship with the dependent variable. Therefore, the S variable does not have a significant influence on this model. The variable O has a coefficient of 0.57525 and a Pr(> |z|) value of 0.0202. This coefficient indicates that for every increase in variable O, the log odds of the dependent variable increase by 0.57525. A Pr(> |z|) value lower than 0.05 signifies a statistically significant relationship, suggesting that variable O has a significant impact on this model. The coefficient of variable D is -0.32425, indicating that each increase in variable D will result in a decrease of 0.32425 in the log probability of the dependent variable. However, the Pr(> |z|) value of 0.1279 suggests that variable D does not have a statistically significant relationship with the dependent variable. Therefore, variable D does not have a significant influence on this model.

In summary, the logistic regression analysis reveals that out of the three independent variables examined, only variable O exerts a substantial impact on the dependent variable, with a confidence level exceeding 95%. The positive and significant coefficient of the variable O implies that there is a statistically significant relationship between an increase in the value of O and an increase in the log odds of the dependent variable. The variables S and D, representing positive and negative influence respectively, do not exhibit a statistically significant correlation with the dependent variable. This indicates that variable O is the only one that has a substantial impact on this logistic regression model, whereas variables S and D do not have a significant impact.

4.2. Evaluation Logistic Regression Model

The confusion matrix evaluates a model by presenting the actual and predicted values in a table format. It includes the true positive rate (TPR), which represents cases where the actual value and predicted value are both 1, the false positive rate (FPR), which represents cases where the actual value is 1 but the prediction is 0, the true negative rate (TNR), which represents cases where both the actual and predicted values are 0, and the false negative rate (FNR), which represents cases where the actual value is 0 but the prediction is 1. The confusion matrix results for the training data and test data are displayed in tables 7 and 8, correspondingly.

Table 7. Data training confusion matrix

Prediction	**Actual**	
	0	**1**
0	2	1
1	12	50

Table 7 presents the confusion matrix results for the training data, indicating 1 false positive rate (FPR) and 12 false negative rates (FNR).

Table 8. Data test Confusion matrix

Prediction	**Actual**	
	0	**1**
0	0	0
1	3	12

In Table 8, the confusion matrix for the test data reveals 3 false negative rates (FNRs), where the actual data is 0 but the model predicts it as 1. Consequently, the total number of incorrect predictions made by this model amounts to 16. The model has a misclassification error rate of 20%. Misclassification error refers to the occurrence of an error in data classification, where a model inaccurately predicts the processed data. Misclassification error can serve as a measure of the accuracy of the predicted regression model. A lower misclassification error number indicates a higher quality of the created model (Bhattacharjee et al., 2020).

In addition to evaluating the confusion matrix and misclassification error, receiver operating characteristic (ROC) analysis was also conducted. The Receiver Operating Characteristic (ROC) is a metric that quantifies the performance of classification models. The Receiver Operating Characteristic (ROC) is shown by a graphical curve that illustrates the Area Under the Curve (AUC), which measures the logistic regression model's capacity to distinguish between failure and non-failure classes. The Receiver Operating Characteristic (ROC) curve is generated by plotting the True Positive Rate (TPR) on the y-axis and the False Positive Rate (FPR) on the x-axis. The R processing results indicate an AUC value of 72%. According to Bhattacharjee et al. (2020), a logistic regression equation demonstrates a good fit to the model if the area under the ROC is above 50%. Thus, the model can thereafter be employed for the purpose of risk prioritisation.

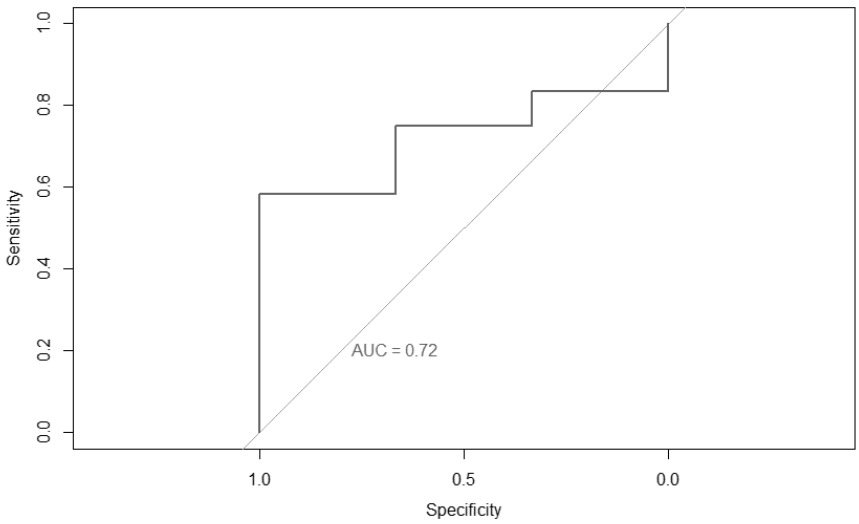

Figure 4. ROC curve

Table 9. Risk priority result

FM	Probability of failure
FM2	87.11%
FM7	82.14%
FM10	81.65%
FM9	79.82%
FM6	79.18%
FM1	78.92%
FM3	75.89%
FM4	75.32%
FM8	72.52%
FM5	67.32%

4.3. The probability of risk of failure

The model is used to get the probability of risk of failure, which is obtained by using the following equation:

$$e^y = \frac{P}{1-P} \quad (4)$$

$$P = \frac{e^{\beta_0 + \beta_1 S + \beta_2 O + \beta_3 D}}{(1 + e^{\beta_0 + \beta_1 S + \beta_2 O + \beta_3 D})} \quad (5)$$

PFMs are organised based on the probability of failure risk. Therefore, the model will assist the management in suggesting appropriate measures to address the issue (Bhattacharjee et al., 2020).

Table 9 shows risk prioritization based on probability of failure, which will recommend to management which risks need to be prioritized based on the numbers calculated from the model. Expert opinions are collected to determine appropriate mitigation to overcome/avoid these risks that may occur which are arranged in Table 10.

Table 10. Propose risk mitigation

Risk priority	Failure mode/Risk	Mitigation
1	Manufacturing defect (FM2)	Ensure that the provider has tested all materials, especially the main material before delivery to the location, and also ensure that the manufacturer will provide a material guarantee as required
2	Incompetent operation officer (FM7)	Especially in isolated locations, with minimal experience and knowledge, it is necessary to provide in-depth training for the operation, troubleshooting and maintenance of PV power plant
3	Equipment failures (FM6)	Operating according to SOP; carry out upskilling of operators and related fields to increase competence and understanding regarding operation, troubleshooting and maintenance of power plants
4	Periodic maintenance not performed (FM10)	Establish a routine OH schedule set by the company and supervised by the manufacturer
5	Incompetent maintenance officer (FM9)	Carry out maintenance briefings for operators and related fields and schedule regular maintenance to ensure the generator does not experience problems and can operate optimally
6	ncompatibility of component specifications (FM1)	Ensure that the component specifications designed by the implementing partner are in accordance with the specifications required in the contract; recruiting consultants to conduct design reviews before implementation
7	Installation error (FM4)	Ensure installation is carried out by experts, carry out control functions, carry out performance tests according to regulations
8	Solar variabbility (FM8)	Field survey before installation, software simulation at the beginning of planning
9	Lack of contractor commitment (FM3)	Ensure providers and field implementation partners have experience in this field, as well as carry out regular monitoring and evaluation to mitigate obstacles that occur.
10	Applicability in regions with specific climatic conditions (FM5)	Ensure that the land selected meets the criteria, during land clearing ensure that there is no shading interference such as from trees or other buildings, apart from that the positioning of the PV module is adjusted to the cardinal direction and slope level.

Table 9 displays the outcomes of the evaluation and computation of the likelihood of failure. A total of 10 risk rankings were calculated, with the highest percentage of probability of failure being assigned the top ranking and the lowest % being assigned the lowest ranking. The highest risk rating is assigned to the occurrence of PV powerplant components with manufacturing/production defects. This indicates that mitigating this risk should be prioritised. Other risks to consider include operators who lack competence in operating the PV powerplant, failure to perform regular periodic maintenance, maintenance officers who are less competent in their duties, and component damage resulting from operation. FM5 represents an installation environment that is not suitable, which is the risk with the lowest priority. This indicates that addressing this risk quickly is not a priority. Prior to constructing the PV powerplant, environmental assessments are conducted to limit the danger of an unsuitable installation environment and ensure the dependability of the installed equipment. Among the top 5 prioritised risks, three align with the findings of a study conducted in Kerala, India by Mohamed et al. in 2019.

These three major risks include the scarcity of proficient technicians for operations, the risk associated with periodic maintenance, and the shortage of skilled technicians for maintenance. Within the research, the primary risk identified was the limited availability of proficient technicians for operation. However, in this particular study, this risk was ranked as the second priority. Conversely, the risk associated with periodic maintenance was ranked fourth in terms of solar power plant risks in Kerala, but in this study, it was considered the third priority. The study conducted by Shojaeimehr & Rahmani (2022) categorises the risk of difficulty in obtaining workers in remote areas as a semi-critical. In contrast, this study ranks the risk of the availability of skilled technicians for maintenance as the third priority risk, whereas it is ranked fifth in the previous study. The primary risk priority is associated with trained labour due to the solar power plant's position in a remote and isolated area, apart from the electricity network. The labour force utilised for operations and maintenance consists of local labourers from the surrounding area. The generator is situated. The workforce comprises local individuals who have undergone training to perform activities at the factory, rather than experienced experts. This is anticipated to increase management's focus on prioritising high-priority risks, such as workforce issues. Component damage, which is ranked fifth in terms of importance in this research, is also identified as a danger of semi-critical level in a study conducted by Shojaeimehr & Rahmani in 2022. In addition, there has been substantial research on the specific and technical damage to components, including studies conducted by Rajput et al. (2019), Bansal et al. (2021), Akram et al. (2022), and others. Akram et al. (2022) identified a sequential pattern of component deterioration in solar power plants. The damage begins with the encapsulant, followed by damage or fractures in the panel backsheet, cracks in the solar cells, damage to interconnections, and the formation of hotspons due to the presence of a dirty module. According to a study conducted by Rajput et al. in 2019, it has been found that discolouration of Ethyl Vinyl Acetate (EVA) is a frequent type of damage that leads to failure in Photovoltaic Laminate Sheets. Other types of damage that occur in PV powerplant include hot spots, encapsulant delamination, backsheet delamination, and corrosion of the solder joints. Each failure mode is evaluated and ranked according to the corresponding mitigation strategy that will be implemented to address each potential risk.

Mitigation strategies are developed based on the specific operational conditions in the field and draw upon the expertise of professionals experienced in managing PV power plant. The risk mitigation measures, organised according to their respective risk priority, are shown in table 10.

5. Conclusions

This study employs the Failure Mode and Effects Analysis (FMEA) risk assessment method, which is combined with the logistic regression method, to address the limitations of the traditional FMEA method. Specifically, it calculates the relative weights of severity, occurrence, and detection attributes/variables. The logistic regression model was constructed with a misclassification error rate of 20% and an area under the curve (AUC) of 72%.

According to the research findings, it can be inferred that there are 10 potential risks associated with optimising PLTS operations to prevent failure or damage to PLTS. These risks arise from the 5 stages of the operation process, namely planning and procurement, installation, and operation and maintenance.

The primary hazards that lead to damage in PV powerplant with a lifespan of less than 25 years and a capacity factor (CF) below 17% are ranked according to the top five priorities. These include manufacturing/production defects in PLTS components, operators lacking competence in operating PLTS, irregular performance of periodic maintenance, inadequately skilled maintenance personnel, and component damage resulting from operations.

Risk rankings and mitigation are generated to prioritize actions aimed at limiting the occurrence of failure/damage and low-capacity factors in photovoltaic power plants as recommendations for the management

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