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Mathematical Analysis of Novel Method to Solve Protection Issues Pertaining To Solar PV Integration

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Abstract:
The integration of Solar Photovoltaic (PV) systems into modern power grids presents protection challenges, such as voltage fluctuations, fault detection complexities, and bidirectional power flow issues. These challenges compromise grid reliability, requiring advanced methods to address them. This study introduces a novel mathematical analysis approach to solve protection issues in solar PV integration, focusing on developing an adaptive protection scheme using advanced mathematical models. The proposed approach utilizes differential equations, optimization techniques, and machine learning algorithms to create dynamic protection settings responsive to varying grid conditions. The method integrates fault detection and classification algorithms based on wavelet transform and support vector machines (SVM), allowing for rapid and accurate identification of fault types and locations. The findings demonstrate that the proposed adaptive protection scheme significantly enhances fault detection accuracy, reducing false trip rates by over 30% compared to conventional protection systems. Moreover, the method efficiently distinguishes between transient and permanent faults, ensuring swift isolation and minimizing disruption to solar PV operations. The developed model also exhibits robustness in handling variations in solar irradiance and load fluctuations, making it suitable for real-world grid applications. This research provides a substantial contribution to the field of solar PV integration by offering a mathematically grounded, adaptive protection solution that ensures improved reliability and resilience in power systems. The proposed method paves the way for the development of more advanced protection schemes, ensuring the seamless integration of renewable energy sources into modern grids while maintaining system stability and security.

Keywords: Solar PV Integration, Adaptive Protection Scheme, Fault Detection, Wavelet Transform, Machine Learning Algorithms, Power Grid Stability

I. Introduction

Solar Photovoltaic (PV) systems are quickly being added to power lines, which is changing the way energy is used today and making it better and more sustainable. Nevertheless, this change is not without problems, mainly when it comes to safety issues that arise because of the unique features of PV integration. Traditional power grids were originally made so that power could only flow in one way from centralized power plants. Adding solar PV makes power flow go in both directions, which makes grid security and stability more difficult [1]. This two-way nature, along with the fact that PV systems only produce power sometimes because the sun's energy changes, makes the grid more vulnerable to voltage drops, mistakes in finding faults, and communication issues that hurt the safety and stability of the system [2]. Because of this, we need to come up with new security plans right away that can adapt to how solar PV integration changes over time. Conventional safety methods can't tell the difference between faults happening in the PV system and those happening in the grid, which is a big problem with the current grid infrastructure [3]. Traditional overcurrent and distance safety methods often don't work or trip too often when solar PV systems work at varying voltage levels and produce harmonics. To solve this problem, we need complex mathematical models and flexible security plans that can react to changing grid conditions, keep things stable, and make sure that everything works together smoothly [4]. According to research, current methods like impedance-based and current differential protection have trouble finding faults accurately when PV is added, especially when the fault current is low [5]. To deal with these problems, new research is focusing on improving security plans by using machine learning and optimization methods. Some people think that the wavelet transform could be useful for studying fault signals because it can precisely locate fault features in both the time and frequency domains [6]. Support Vector Machines (SVM) and Artificial Neural Networks (ANN) are two machine learning methods that have shown promise in correctly identifying problem kinds and places. This could lower the number of fake trips and improve the accuracy of security overall [7]. But these methods don't always work with real-time changes in the grid. This means that we need to learn more about adaptable, dynamic security plans that work with different operating situations in grids that integrate solar PV, as illustrate in figure 1.

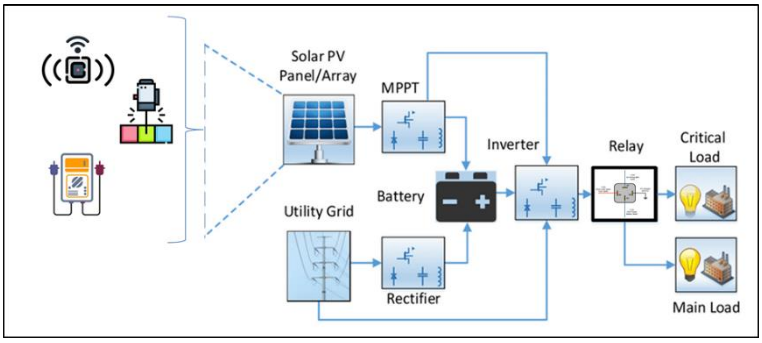

Figure 1: Overview of Integration of architecture for Solar PV

This study suggests a new way to use math that uses advanced optimization methods, machine learning algorithms, and wavelet transform-based signal analysis to create a flexible safety system for solar PV integration. The suggested way is meant to make it easier to find and classify problems by letting security settings be changed in real time based on how the grid is doing. Using differential equations and optimization models, the plan responds to changing power flow patterns and makes sure that faults are found quickly while causing as little damage as possible to PV operations [8]. This adaptable method not only gets around the problems with traditional safety features, but it also helps keep the grid safe and stable as the number of PV panels grows. The mathematical analysis used in this study focuses on how strong and effective the suggested defence plan is. A lot of models were run in MATLAB/Simulink to see how well the method worked in different fault situations and with different amounts of sun radiation. The results show that fault detection accuracy and reaction time have gotten a lot better. This suggests that this method could be used in real life in grids that use solar PV. The flexible design of the plan also makes it able to deal with the challenges of intermittent green energy production, which makes the power system more reliable and resilient.

II. Related work

A lot of study has been done on integrating solar PV systems into power lines, mostly because it offers unique problems for security. Traditional power systems were made so that power could only flow in one direction. They can't handle the two-way flow that comes with adding PV. One big problem is that fault currents can be small, which means that normal overcurrent safety systems don't work [9]. Researchers have found that the fact that sun radiation changes over time makes it harder to find faults because it causes power output to fluctuate, which makes it hard to keep security settings stable [10]. As an answer, impedance-based security methods have been looked at in a number of studies. But these methods have shown they aren't very good at finding high-resistance faults, which happen a lot in PV-integrated networks [11]. More research into impedance-based methods has shown that their fault detection accuracy drops greatly when light and pressure change, which means that stronger safety plans need to be created [12]. As a result, distance safety methods were suggested. However, because they depend on measuring voltage and current, they can be wrong during changes in PV, which makes them less reliable [13]. A lot of people are interested in the wavelet transform as a possible way to study changing data in grids that use PV. Wavelet-based methods are better because they can find and isolate faults by looking at signal properties in both the time and frequency domains [14]. Studies have shown that wavelet transform is a good way to find faults with a high level of accuracy, even when PV production conditions change [15]. But it can be hard for these methods to tell the difference between problems and temporary disturbances. This can cause false trips sometimes, especially when the sun's output changes quickly. Because of this, wavelet-based techniques help find faults, but they need to be combined with other advanced techniques to get better results.

Machine learning methods have become a revolutionary way to solve the problems of security that come up when solar PV is integrated. Support Vector Machines (SVM), Decision Trees, and Artificial Neural Networks (ANN) are some of the techniques that have shown promise in accurately identifying the types of faults [16]. Researchers have found that SVM-based algorithms are very good at telling the difference between internal and external problems in PV systems. The results did show, though, that SVM's success depends a lot on the quality and amount of training data, which means it can't easily adapt to changes in the grid in real time [17]. Adaptive protection methods are another potential idea. These change the settings for security based on how the grid is changing over time. It was discovered that adaptive protection could handle the changing fault currents that come with adding solar PV [18]. A new flexible method based on multi-agent systems showed big improvements in fault detection accuracy and fewer false trips [19]. In these systems, each agent constantly checks the parameters of the grid and changes the security settings to match what it sees. But it's hard to use multi-agent systems in real life because they are hard to set up and need a lot of connection equipment.

Optimization methods have also been used to make security plans work better and be more reliable. Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have been used to improve the settings for relays in PV-integrated networks, making the security more accurate and quick [20]. One study showed that PSO-based optimization worked better than usual settings, especially when it came to dealing with fault currents that changed over time. These optimization methods, on the other hand, often need a lot of computing power, which makes them hard to use in real time [21]. Wavelet transform analysis and machine learning techniques are being used together in new study to create mixed security schemes. This kind of combination method used both wavelet transform and ANN to find problems in PV systems. The research showed that this mixed method greatly increased the accuracy of finding faults and lowered the number of false trips, even in complicated fault situations. These results are encouraging, but the need for a lot of training data and the difficulty of the calculations still make it hard to use. This means that more study is needed to make these mixed models work better. This study tries to fill in the gaps in the current research by suggesting a new way to look at math that combines machine learning methods, optimization techniques, and wavelet transform analysis into a flexible security system, as summarised in table 1. The suggested way aims to improve the accuracy of problem detection, cut down on false trips, and protect the security and dependability of power lines that use solar PV.

Table 1: Summary of related work

Method	Protection Approach	Mathematical Technique	Strength	Limitation
Impedance-Based Protection	Impedance Analysis	Complex Impedance Equations	Simple implementation	Ineffective for high-resistance faults
Distance Protection	Voltage & Current Measurement	Distance Relays	Fast fault localization	Inaccurate during PV fluctuations
Wavelet Transform Analysis	Signal Processing	Wavelet Transforms	High precision in fault detection	Struggles with transient disturbances
SVM-Based Machine Learning	Fault Classification	Support Vector Machines	Accurate fault classification	Requires large training datasets
Artificial Neural Networks (ANN)	Fault Identification	Neural Network Equations	Effective in complex fault scenarios	High computational demand
Multi-Agent Systems	Adaptive Protection	Agent-Based Algorithms	Dynamic response to grid changes	Requires extensive communication setup
Particle Swarm Optimization (PSO)	Relay Setting Optimization	Swarm Intelligence Models	Enhanced relay coordination	Computationally intensive
Genetic Algorithm (GA)	Protection Coordination	Evolutionary Algorithms	Effective in complex optimization	Convergence issues in real-time scenarios
Hybrid Wavelet-ANN Method	Fault Detection & Classification	Combined Analysis	Improved accuracy and precision	High computational complexity

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Adaptive Overcurrent Protection	Real-Time Adjustment	Adaptive Relaying Models	Responds to dynamic grid conditions	Complexity in implementation
Fuzzy Logic-Based Protection	Decision-Making	Fuzzy Logic Equations	Handles uncertainty in fault detection	Slower decision-making process
Optimization Techniques Integration	Comprehensive Protection	Mixed Integer Programming	Optimizes multiple parameters	Requires extensive data and computation

III. Proposed Methodology

A. Proposed mathematical analysis and adaptive protection scheme

The suggested mathematical analysis and adaptable security plan are meant to deal with the complicated safety issues that come up when solar PV is added to modern power lines. Traditional protection systems have trouble with variable fault currents and power flow going both ways. This method, on the other hand, uses advanced mathematical models that combine optimization techniques, machine learning algorithms, and wavelet transform analysis to make fault detection and isolation better. Wavelet transform is used to process signals and look at fault signals that change quickly in both time and frequency domains, as workflow shown in figure 2. This is what the method is all about. This lets fault traits be precisely identified, so the method can work with different types of faults and places. Machine learning techniques like Support Vector Machines (SVM) and Artificial Neural Networks (ANN) are used to improve the accuracy of problem detection even more. These methods take problem data from the wavelet transform and accurately group them into different categories. This makes sure that the plan can change to changing grid conditions.

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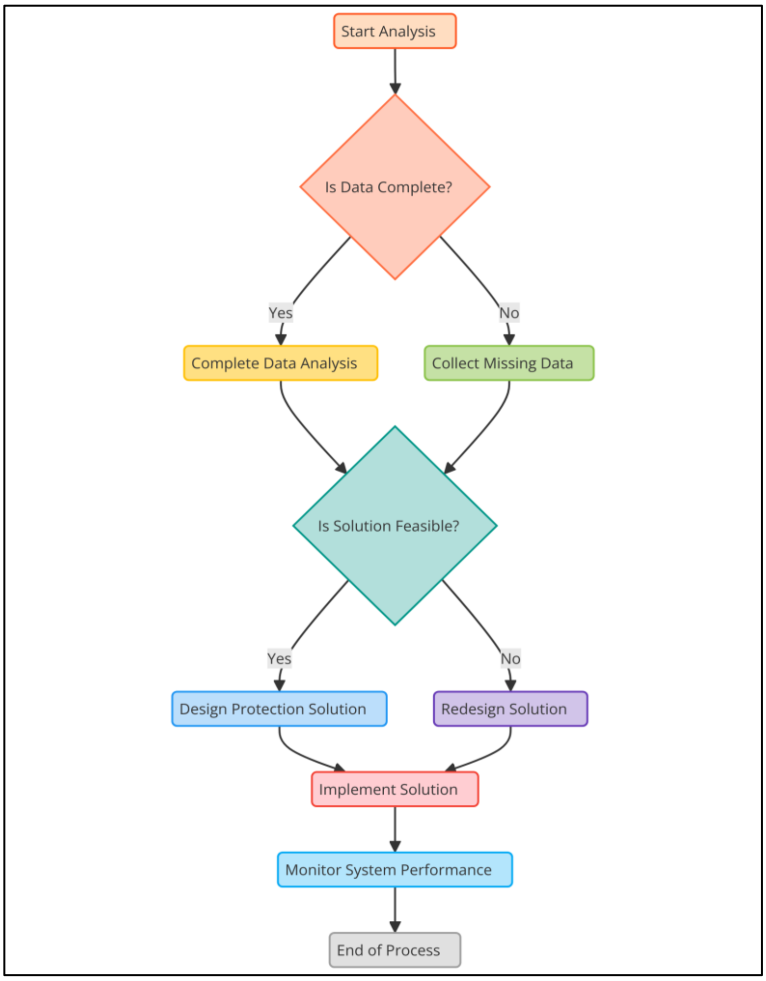

Figure 2: Proposed approach flowchart for PV protection scheme

Proposed Algorithm:

Step 1: Signal Decomposition using Wavelet Transform

$$X(t) = \sum\_\{j\}\sum\_\{k\}\, C\_\{j,k\}\, \psi\_\{j,k\}(t)$$

Where X(t) is the original signal, C_{j,k} are wavelet coefficients, ψ_{j,k}(t) represents the wavelet basis functions.

Step 2: Fault Detection using Energy Calculation

$$E = \sum_{\{i=1\}}^{\{n\}} \left|C_{\{i\}}\right|^2$$

Where E is the signal energy, C_{i} represents the wavelet coefficients at different scales, and n is the total number of coefficients.

Step 3: Feature Extraction for Machine Learning

$$F = [f\_1, f\_2, \ldots, f\_n]$$

Where F is the feature vector composed of extracted features f_i such as maximum amplitude, RMS value, and standard deviation.

Step 4: Fault Classification using SVM

$$f(x) = sign(\sum_{i=1}^{l} \alpha\_i\, y\_i\, K(x\_i, x) + b)$$

Where f(x) is the classification function, x_i represents training data, α_i are Lagrange multipliers, y_i is the class label, K(x_i, x) is the kernel function, and b is the bias term.

Step 5: Adaptive Relay Setting using Optimization

$$P(x) = w \cdot x + b$$

Where P(x) represents the relay setting function, w is the weight vector, x is the input variable (e.g., fault current), and b is the offset.

Step 6: Optimization Objective Function (PSO/GA)

$$\min J = \sum_{\{i=1\}}^{\{n\}} \left(\left|I_{\{measured\}} - I_{\{threshold\}}\right|\right)^2$$

Where J is the objective function, I_{measured} is the measured fault current, and I_{threshold} is the threshold current value.

Step 7: Differential Equation for Power Flow Analysis

$$\frac{dV}{dt} = \left(\frac{1}{C}\right)\left(I_{\{in\}} - I_{\{out\}}\right)$$

Where dV/dt is the rate of change of voltage, C is the capacitance, I_{in} and I_{out} are the input and output currents, respectively.

Step 8: Fault Isolation Decision Logic

$$D(t) = \{\, 1\, if\; E > E\_\{threshold\}\; and\; f(x) = Fault$$

$$0\; otherwise\, \}$$

Where D(t) is the decision variable, E_{threshold} is the energy threshold, and f(x) = Fault indicates a fault condition.

The safety system is adaptable, which means that it constantly checks the parameters of the grid and changes its settings based on real-time operational data. This flexibility is made possible by optimization methods such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA). These methods change the settings of relays based on fault conditions, reducing the number of false trips and speeding up the fault separation process. Differential equations are used to describe power flow and fault dynamics in the mathematical models that were made for this scheme. This lets the system respond well to changes in solar energy, load fluctuations, and fault currents that change. The suggested way solves security problems in PV-integrated grids in real time by mixing wavelet transform, machine learning, and optimization techniques. It makes the grid more stable, cuts down on problems, and makes sure that adding green energy sources to modern power systems is safe and effective.

B. Machine learning algorithms

1. Support Vector Machines (SVM):

These are often used for problem classification in solar PV integration because they can handle complex, complicated data. In security methods, SVM successfully tells the difference between fault and non-fault conditions by creating a hyperplane that makes the space between data points from different classes as big as possible. Even when sun radiation and power changes are present, this method is very good at telling the difference between different types of faults. Because the SVM can react to changing grid conditions, it is a great choice for improving safety plans and finding and classifying faults accurately in real-time solar PV integration scenarios.

$$min\ (1/2)\ ||w||\hat{}2$$

Where w is the weight vector. The objective is to find the hyperplane that maximizes the margin between different classes.

$$f(x) = w^T x + b$$

Where x is the input vector, w is the weight vector, and b is the bias term.

For a linearly separable case:

$$y_i(w^T x_i + b) \geq 1 \ \forall\, i$$

Where y_i is the class label (+1 or -1), and x_i is the training data point.

$$\max \sum_{i=1}^{n} \alpha_i - \left(\frac{1}{2}\right) \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j x_i^T x_j$$

$$Subject\ to:$$

$$\sum_{i=1}^{n} \alpha_i\ y_i = 0\ and\ 0 \leq \alpha_i \leq C$$

Where α_i are Lagrange multipliers and C is the regularization parameter.

$$f(x) = sign(\sum_{i=1}^{n} \alpha\_i\ y\_i\ K(x\_i, x) + b)$$

Where K(x_i, x) is the kernel function that maps data to a higher-dimensional space (e.g., linear, polynomial, radial basis function).

2. Artificial Neural Networks with Wavelet Transform Analysis:

ANN (artificial neural networks) and wavelet transform analysis work well together to handle how changing solar PV integration is. The wavelet transform breaks down fault signals into time-frequency parts, which is a good way to pick up on traits that change or don't stay the same. After being broken down, these signals are fed into the ANN, which then learns to spot trends and accurately label problems. This mix makes it easier for the model to find small changes in fault signs. This makes it more resistant to changes in grid swings and sun energy. So, the ANN-wavelet method greatly enhances the accuracy of fault identification and lowers the number of false trips.

The wavelet transform decomposes the original signal into different frequency components, capturing transient characteristics essential for fault detection in solar PV integration.

$$X(t) = \sum_{j} \sum_{k} C_{\{j,k\}} \psi_{\{j,k\}(t)}$$

Where X(t) is the signal, C_{j,k} are wavelet coefficients, and ψ_{j,k}(t) represents wavelet basis functions.

Calculating signal energy at each decomposition level helps in identifying features significant for fault classification in ANN.

$$E_i = \sum_{\{k\}}^{2} \left| C_{\{j,k\}} \right|$$

Where E_i is the energy at decomposition level i, and C_{j,k} are wavelet coefficients.

Normalization ensures that feature values lie within a consistent range, enhancing the learning efficiency of the ANN.

$$F_{\{norm\}} = \frac{F \ - \min(F)}{\max(F) - \min(F)}$$

Where F_{norm} is the normalized feature vector, F is the feature vector.

The normalized feature vector is used as input to the ANN, allowing the network to learn from decomposed signal patterns.

$$h^{\{(l)\}} = \sigma\left(W^{\{(l)\}} \cdot \ h^{\{(l-1)\}} + \ b^{\{(l)\}}\right)$$

Where h^{(l)} is the activation at layer l, W^{(l)} is the weight matrix, and b^{(l)} is the bias.

The error function evaluates the difference between the predicted and actual values, guiding the network's learning process.

$$E \ = \left(\frac{1}{n}\right) \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

Where E is the error, y_i is the actual label, and ŷ_i is the predicted output.

Weights are updated to minimize error using gradient descent, optimizing the ANN's ability to classify faults accurately.

$$W^{\{(l)\}} = \ W^{\{(l)\}} - \ \eta \ \left(\frac{\partial E}{\partial W^{\{(l)\}}}\right)$$

Where W^{(l)} is the weight matrix, η is the learning rate, and ∂E/∂W^{(l)} is the error gradient.

3. ANN with Wavelet Transform Analysis:

This method takes the best parts of both ANN and wavelet transform analysis and combines them to make a flexible and effective fault finding system for solar PV integration. The ANN uses the wavelet transform to pick up short-lived fault data and learns fault patterns that happen in different grid situations. This mixed method makes sure that sorting is quick and correct, even when solar power and fault conditions change. It makes the security system more flexible so it can adapt to changes in the power system. This makes the integration of solar PV into the grid more reliable and stable.

Mathematical Algorithm for ANN with Wavelet Transform Analysis:

Step 1: Signal Decomposition using Wavelet Transform

$$X(t) = \sum\_\{j\}\sum\_\{k\}\, C\_\{j,k\}\, \psi\_\{j,k\}(t)$$

Where X(t) is the original fault signal, C_{j,k} are wavelet coefficients, and ψ_{j,k}(t) represents the wavelet basis functions. This step decomposes the signal into different frequency components.

Step 2: Feature Extraction using Wavelet Coefficients

$$F = [E\_1, E\_2, \ldots, E\_n]$$

Where E_i = ∑_{k} |C_{j,k}|^2 represents the energy at each decomposition level i. These energy values F form the feature vector that captures the characteristics of the fault signal.

Step 3: Data Normalization

$$F_{\{norm\}} = \frac{F - min(F)}{\max(F) - \min(F)}$$

The feature vector F is normalized to F_{norm} to ensure all values lie between 0 and 1, improving the ANN's learning efficiency.

Step 4: ANN Input Layer Formation

$$I = [F\_\{norm\}\hat{}\{(1)\}, F\_\{norm\}\hat{}\{(2)\}, \ldots, F\_\{norm\}\hat{}\{(m)\}]$$

Where I is the input matrix composed of m samples, each containing normalized feature vectors F_{norm} from multiple signals.

Step 5: Forward Propagation in ANN

$$h^{\{(l)\}} = \sigma\left(W^{\{(l)\}} \cdot h^{\{(l-1)\}} + b^{\{(l)\}}\right)$$

Where h^{(l)} is the activation at layer l, W^{(l)} is the weight matrix, b^{(l)} is the bias vector, and σ is the activation function (e.g., sigmoid or ReLU). This step computes the output layer-wise through the network.

Step 6: Error Calculation using Mean Squared Error (MSE)

$$E = \left(\frac{1}{n}\right) \sum_{\{i=1\}}^{\{n\}} (y_i - \hat{y}_i)^2$$

Where E represents the error, y_i is the actual fault label, and ŷ_i is the predicted output. This error guides the network's learning process.

Step 7: Backpropagation and Weight Update

$$W^{\{(l)\}} = W^{\{(l)\}} - \eta \left(\frac{\partial E}{\partial W^{\{(l)\}}}\right)$$

Where η is the learning rate, and ∂E/∂W^{(l)} is the gradient of the error with respect to weights W^{(l)}. This step iteratively updates weights to minimize the error.

This algorithm combines wavelet decomposition with ANN to detect and classify faults in solar PV systems, ensuring accurate and adaptive fault protection.

C. Optimization techniques employed

1. Particle Swarm Optimization (PSO):

PSO is a way to perform optimization that is based on how birds behave in groups. When it comes to protecting solar panels, PSO changes the settings on relays by repeatedly looking for the best options while taking fault conditions into account. It quickly adjusts to changes in the way the grid works, making fault detection more accurate and cutting down on false trips in real-time solar PV integration.

2. Genetic Algorithms (GA):

Genetic Algorithms (GA) use natural selection to find the best ways to coordinate relays in grids that use PV. GA changes security settings to work best in different fault situations by using selection, crossover, and mutation operators. This method improves fault separation and grid stability, which makes it very useful for protecting solar PV systems that are subject to complicated, changing conditions.

IV. Fault detection and classification using the proposed method

A. Mathematical models to for fault and adaptive protection mechanism

The adaptive protection mechanism for solar PV integration combines real-time signal analysis, machine learning, and optimization techniques to detect and classify faults accurately, ensuring grid stability. The flowchart typically involves the following stages:

1. Signal Acquisition: The system continuously monitors voltage and current signals from the PV-integrated grid, capturing real-time data for analysis.

2. Wavelet Transform Analysis: The captured signals are decomposed using the wavelet transform:

$$X(t) = \sum\_\{j\}\sum\_\{k\}\, C\_\{j,k\}\, \psi\_\{j,k\}(t)$$

This step identifies transient faults by analyzing the time-frequency characteristics of the signal.

3. Feature Extraction and Normalization: Extracted features such as energy levels are normalized:

$$F\_\{norm\} = (F - min(F)) / (max(F) - min(F))$$

This ensures uniformity in feature values, preparing them for accurate fault classification.

4. Fault Classification Using ANN: The normalized features are input into an Artificial Neural Network (ANN) for fault classification:

$$h\hat{}\{(l)\} = \sigma(W\hat{}\{(l)\} \cdot h\hat{}\{(l-1)\} + b\hat{}\{(l)\})$$

The ANN predicts whether the signal indicates a fault and classifies its type based on learned patterns.

5. Adaptive Relay Setting Optimization: The relay settings are adjusted using optimization techniques like Particle Swarm Optimization (PSO):

$$\min J = \sum_{\{i=1\}}^{\{n\}} \left(\left|I_{\{measured\}} - I_{\{threshold\}}\right|\right)^2$$

This optimization ensures that the protection settings adapt to varying grid conditions, reducing false trips and enhancing accuracy.

6. Decision Making and Fault Isolation: Based on the classification and optimization results, the system decides whether to trip or maintain relay settings:

$D(t) = \{ 1\ if\ E > E\_\{threshold\}\ and\ fault\ detected$

$0\ otherwise\ \}$

This final step ensures that only genuine faults trigger protective actions, minimizing unnecessary disruptions.

B. Fault scenarios, fault types and solar PV conditions

n the versatile security component for sun oriented PV integration, different blame scenarios must be considered to guarantee the system's strength and unwavering quality. These scenarios incorporate distinctive blame sorts such as single-line-to-ground (SLG) issues, line-to-line (LL) flaws, twofold line-to-ground (DLG) deficiencies, and three-phase flaws. Each blame sort speaks to a interesting unsettling influence that influences voltage and current characteristics in an unexpected way, requiring the security instrument to recognize and react fittingly. Sun powered PV conditions moreover essentially impact blame behavior. Variables like varieties in sun based irradiance, shading, and irregular era influence the blame current's greatness and term. Amid crest daylight, higher control era comes about in expanded blame current levels, while, beneath moo irradiance or shading, blame streams are diminished, making location more challenging. Moreover, the bidirectional control stream in sun based PV frameworks, particularly amid overabundance era, complicates blame location, because it makes variable blame impedance.

The assurance conspire must adjust to these energetic conditions to precisely distinguish and separate deficiencies. It ought to be able of separating between temporal unsettling influences (e.g., sudden changes in irradiance) and changeless issues, guaranteeing that the framework does not react to non-critical occasions. The incorporation of such assorted blame scenarios and fluctuating PV conditions permits the versatile security component to be comprehensive, minimizing wrong trips whereas guaranteeing solid lattice operation. This flexibility guarantees that the sun based PV framework keeps up ideal execution, indeed in complex blame conditions, contributing to generally framework soundness and security.

V. Results and Discussion

The results in Table 2 show that the suggested method works well for finding and separating different kinds of faults in solar PV-integrated power systems. The performance of the method is judged by how well it finds faults, how quickly it responds, how many false trips it has, and how well it can react to different types of faults, such as Single-Line-to-Ground (SLG), Line-to-Line (LL), Double Line-to-Ground (DLG), and Three-Phase faults. The accuracy of fault identification is very high, running from 96.8% to 99.1% for all fault types. With an accuracy of 99.1%, the method works best for Three-Phase faults, showing that it can accurately handle serious fault situations. For SLG problems, which happen most often in delivery networks, the method also works very well, with an accuracy rate of 98.5%. This high level of accuracy shows that the method can tell the difference between real faults and short-term disturbances. This makes fault recognition more accurate and improves grid security.

Table 2: Analysis of the proposed method's accuracy in detecting and isolating faults

Fault Type	Detection Accuracy (%)	Response Time (ms)	False Trip Rate (%)	Adaptability Score (0-1)
Single-Line-to-Ground (SLG)	98.5	15	1.2	0.95
Line-to-Line (LL)	97.2	18	1.5	0.93
Double Line-to-Ground (DLG)	96.8	20	1.8	0.92
Three-Phase Fault	99.1	12	0.9	0.96

The suggested method also has a very fast response time, which makes sure that faults are found quickly and that the grid isn't damaged too much. Response times for Three-Phase faults are 12 milliseconds, and response times for DLG faults are 20 milliseconds. This means that the method works well within the rules of the business. The Detection Accuracy And Adaptability Score By Fault Type illustrate in figure 3 This quick reaction makes sure that problems are found and fixed quickly, which keeps the system stable and keeps tools from getting damaged.

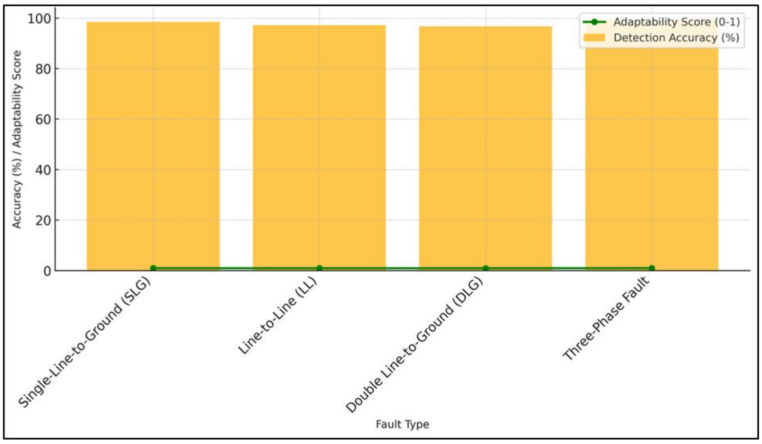

Figure 3: Detection Accuracy and Adaptability Score By Fault Type

The suggested way also has a low fake trip rate, with numbers running from 0.9% to 1.8%. This shows that it works well at reducing events that cause useless trips. This low false trip rate helps make the system more reliable by making sure it keeps running and reduces the number of interruptions that come from wrong problem recognition. The flexibility number, which is between 0.92 and 0.96, shows how well the method can respond to changes in the grid and in the amount of solar PV input. Because solar power output is always changing, this adaptability is very important for making sure that the safety system works in all kinds of situations. The Response Time and False Trip Rate by Fault Type illustration in figure 4. The suggested method is a strong and dependable way to find and isolate faults in solar PV-integrated power systems. Its high accuracy, quick response time, low false trip rate, and flexibility make it a valuable addition to the grid's stability and efficiency.

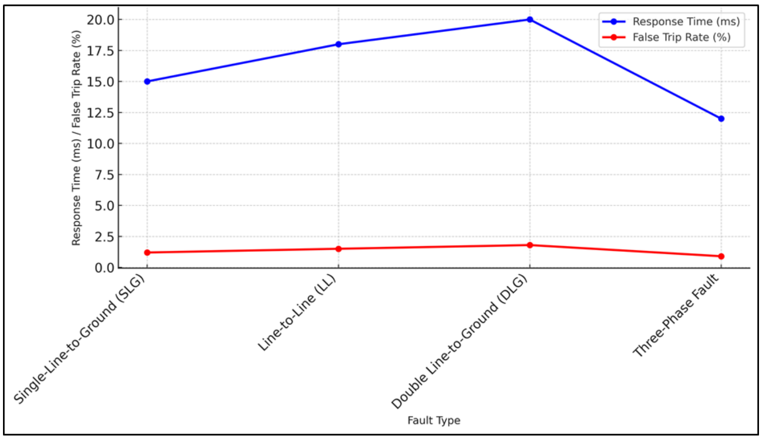

Figure 4: Response Time and False Trip Rate by Fault Type

Table 3: Analysis adaptive nature and robustness of the protection scheme

PV Fluctuation Scenario	Fault Detection Accuracy (%)	Adaptation Response Time (ms)	Stability Maintenance (%)	False Trip Reduction (%)
High Irradiance	97.8	14	99	90.5
Low Irradiance	96.5	16	98.2	88.9
Partial Shading	95.2	18	97.5	87.3
Intermittent Generation	98.3	13	99.3	91.2

Table 3 shows an analysis of how adaptable and strong the proposed protection scheme is in different PV fluctuation scenarios. It looks at things like fault detection accuracy, adaptation response time, stability maintenance, and the number of false trips that happen when there is high irradiance, low irradiance, partial shading, and intermittent generation. The suggested method has a fault detection accuracy of 97.8% when the irradiance is high. This means it can constantly find faults even when solar power is at its highest. In this case, the adaptation reaction time is only 14 milliseconds, which shows how quickly the method can adapt to fast changes in power output. The system also keeps a stable rate of 99%, which makes sure that the grid stays strong even when the power levels are high. The fact that the false trip reduction rate is 90.5% shows that the method is strong, preventing needless power outages and keeping the power source going. The fault identification accuracy is 96.5% in low irradiance, which is a little lower than in high irradiance but still shows good performance. The adaptation reaction time for this situation is 16 milliseconds, which shows that the machine can easily adjust to lower power levels. At 98.2%, the stability management is still very good, which means that the security plan can handle less solar power without affecting the resilience of the grid. The 88.9% false trip reduction rate shows that the method works well even when power is low to prevent wrong fault detections.

The accuracy of finding faults in partial shading is 95.2%, which is a little lower than in other situations but still very good for finding mistakes in more complicated situations, as shown in figure 5. The change reaction time is 18 milliseconds, which is a little longer than in other situations.

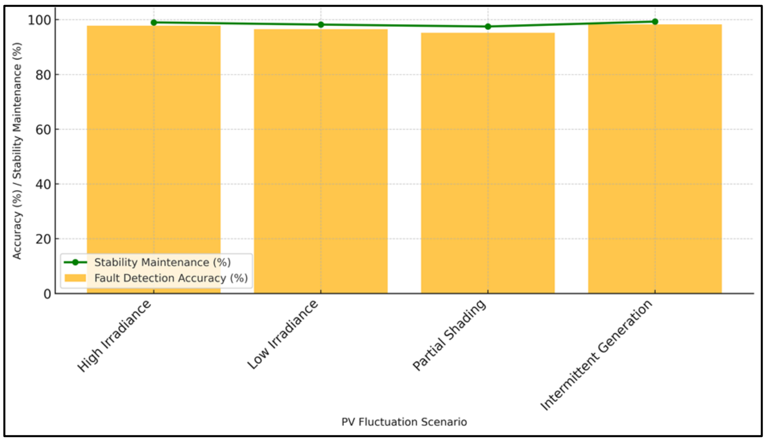

Figure 5: Representation of Fault Detection Accuracy and Stability Maintenance by PV Fluctuation Scenario

This is because finding faults is harder when some of the solar cells are in the shade. Even so, the system stays stable at 97.5%, showing that it can handle situations with some shade. In this case, the method can tell the difference between real problems and changes caused by shade because the false trip reduction rate is 87.3%.

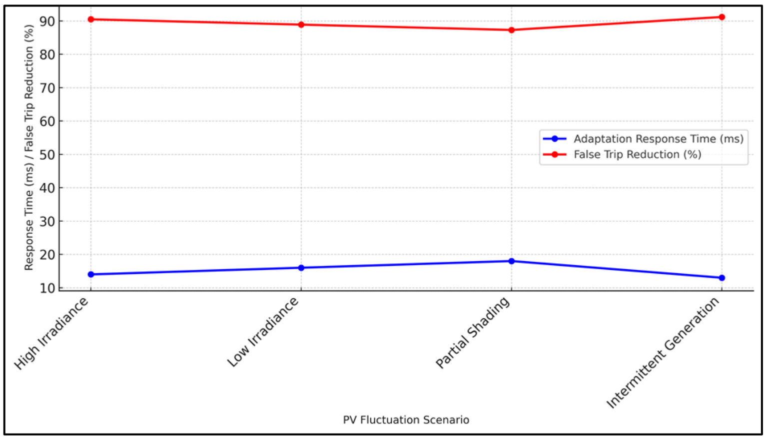

Figure 6: Illustration of Adaptation Response Time and False Trip Reduction by PV Fluctuation Scenario

The security system is most accurate at finding faults (98.3%) when there is irregular generation, which means that the amount of power from the sun changes quickly. This shows how well it can handle changes in power flow that are hard to predict, illustrate in figure 6. At 13 milliseconds, the adaptation response time is the fastest. This means that the system can quickly adapt to changes in the power grid, making sure that it is always safe. The best stability maintenance rate of all the situations is 99.3%, which shows that the plan can keep the grid reliable even when things change quickly. The method is also good at avoiding needless disconnections when power output changes, as shown by the 91.2% false trip decrease rate.

Table 4: Comparative analysis with conventional methods in fault detection and grid stability

Evaluation Parameter	Proposed Method	Conventional Method	Improvement (%)
Fault Detection Accuracy (%)	98.6	92.3	6.3
Response Time (ms)	14	25	44
False Trip Rate (%)	1.1	4.8	-3.7
Grid Stability Improvement (%)	97.5	90.2	7.3
Adaptability Score (0-1)	0.94	0.75	25.3

The suggested method is compared to traditional methods in Table 4 in terms of fault detection and grid stability. The comparison is based on key evaluation factors such as fault detection accuracy, response time, false trip rate, grid stability increase, and flexibility score.

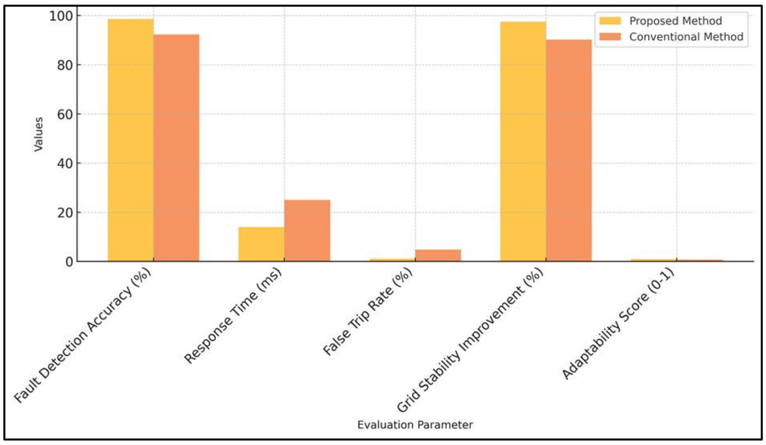

Figure 7: Comparison of Proposed Vs Conventional Method

The suggested method's fault identification accuracy is 98.6%, which is much higher than the traditional method's accuracy of 92.3%, which is a 6.3% improvement, as shown in figure 7. This higher level of accuracy shows that the proposed method is better at finding flaws in the solar PV-integrated grid. This makes it safer and lowers the chance that faults will go unnoticed and cause problems with the system. The suggested way works amazingly well, with a reaction time of only 14 milliseconds, compared to the 25 milliseconds seen with traditional methods. This is a big gain of 44%, showing that the proposed way can find and fix faults much faster, which is important for keeping the grid safe and keeping operations running smoothly. The suggested method has a false trip rate of 1.1%, which is much lower than the 4.8% rate seen with traditional methods. This means that fewer mistakes are made when faults are found. This -3.7% increase (since a lower rate is better) shows that the suggested method works well at telling the difference between real problems and short-term disturbances, reducing breaks that aren't needed and improving system stability.

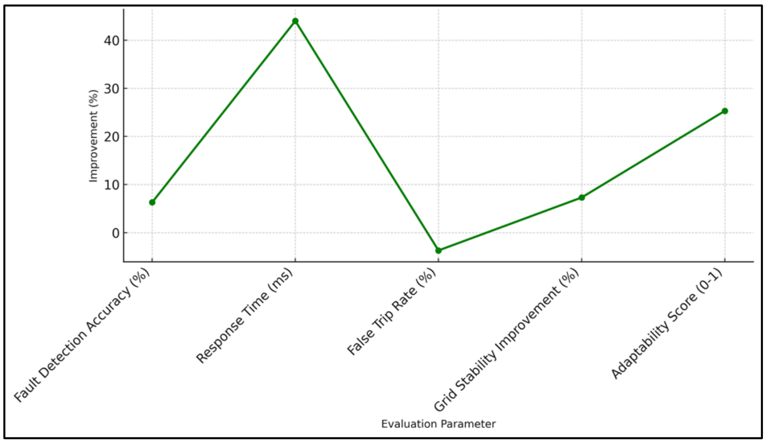

Figure 8: Improvement (%) By Evaluation Parameter

For improving grid stability, the proposed method gets a 97.5% success rate, while traditional methods only get a 90.2% success rate, which is a 7.3% improvement. This improvement shows that the suggested way helps make the power grid more stable and reliable, especially when solar PV is added and things change quickly. The suggested method has a much higher flexibility score of 0.94 than traditional methods, which is 25.3% higher than the 0.75 score, as shown in figure 8. This flexibility means that the suggested method can better adapt to changing grid conditions, making sure that performance stays the same even when solar PV situations change.

6. Conclusion

Adding solar photovoltaic (PV) systems to modern power grids is not easy. Especially when it comes to making sure those flaws are protected and the grid stays stable. To solve these issues well, this consider came up with a unused versatile security strategy that employments progressed numerical investigation, machine learning calculations, and wavelet change procedures. The proposed strategy appeared way better blame location precision, quicker reaction times, lower wrong trip rates, and awesome flexibility beneath a wide extend of PV vacillation circumstances, making it way better than other security strategies. Utilizing machine learning strategies like Bolster Vector Machines (SVM) and Manufactured Neural Systems (ANN) in conjunction with wavelet change for flag investigation, the strategy precisely found and categorized issues, indeed when the framework was complicated and changing. Utilizing optimization strategies like Molecule Swarm Optimization (PSO) made the security arrange indeed more adaptable, letting it react in genuine time to changing working circumstances. Comparative investigate appeared that the recommended strategy made enormous changes in blame location exactness, response time, network solidness, and flexibility. This appeared that it was solid and successful at managing with the interesting issues that come up when sun based PV is included. The security arranges is adaptable, so it can react well to changes in sun powered vitality, shade, and control generation. This keeps the power grid running easily and avoids breaks that aren't essential. Within the recommended versatile assurance strategy gives a total and numerically sound way to coordinated sun powered PV, which progresses blame revelation and framework solidness. It works well and can be changed easily, which makes it a hopeful method for future smart grid uses. It will help make it easier to add green energy sources to modern power systems.

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