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Prediction Analysis of Fault Mode Sets for High Permeability Distributed Energy Distribution Networks Based on Multivariate Data

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Abstract: - This technical abstract describes a prediction analysis methodology for fault mode sets in high-permeability distributed energy distribution networks (DEDNs). DEDNs are complex systems composed of multiple interconnected energy sources, storage units, and loads, which are managed and controlled by intelligent devices. These systems have become increasingly important in modern electricity networks due to their ability to integrate a high share of renewable and distributed energy resources. The proposed prediction analysis aims to identify and classify the various fault modes that can occur in high-permeability DEDNs based on multivariate data. It includes information about the system's operational parameters, such as voltage, current, and frequency, as well as data on weather conditions, load profiles, and the state of the network. The methodology involves collecting and pre-processing the data using suitable techniques, such as data filtering and noise removal.

Keywords: Multiple Interconnected, Intelligent Devices, High-Permeability, Pre-Processing, Distribution Networks, Feature Extraction,Relevant Patterns,Suitable Techniques

1. Introduction

A fault mode set for high permeability distributed energy distribution networks refers to a predefined list of potential faults that could occur within the network and the corresponding actions or protocols that need to be followed to mitigate or resolve those faults [1]. These fault mode sets are essential for ensuring the reliability

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and resilience of distributed energy distribution networks, especially in high permeability settings [2]. In a high permeability distributed energy distribution network, power flows are bidirectional, and distributed energy resources (DERs) are connected to different grid entry points. It creates a complex and dynamic system that requires careful planning and risk management [3]. A fault mode set helps to identify potential weaknesses and vulnerabilities in the network and establish procedures to prevent or mitigate their impacts. The fault mode set for high permeability distributed energy distribution networks may include both technical and operational faults [4]. Technical faults refer to failures in the physical components of the network, such as transformers, circuit breakers, or control systems. Operational faults, on the other hand, are related to human errors, communication failures, or cyber-attacks [5]. The fault mode set should also consider the impact of these faults on the network, such as voltage fluctuations, power outages, or equipment damage [6]. It should identify the necessary actions and responses, such as isolating the affected area, restoring power, or initiating backup systems. The fault mode set should also account for the capabilities and limitations of different DERs and grid technologies, as well as the potential interactions between them during a fault event [7]. Overall, the use of a comprehensive fault mode set is crucial for maintaining the reliability and resiliency of high permeability distributed energy distribution networks, ensuring safe and efficient energy delivery to end users [8]. The Fault Mode Problem Configurations for High Adhesion A problem known as "Distributed Energy Distribution Networks" can arise in contemporary power networks that use a lot of distributed energy resources (DERs), like solar cells, wind turbines, and battery storage [9]. These systems are renowned for having a high permeability, which makes changes and network disturbances readily impact them. Managing fault conditions is a major technical difficulty for these kinds of networks.An aberrant flow of electrical current, usually brought on by a short circuit or overload, is referred to as a fault [10]. Protection mechanisms like circuit breakers, which isolate the problematic network segment to stop equipment damage and guarantee system safety, handle failures in conventional power systems [11]. The fault management procedure in distributed energy distribution networks with high permeability may become more complex when DERs are included. When a failure occurs, DERs may continue to generate power, which may cause a delay in the fault's isolation and discovery[12]. This delay can result in more extended and more severe power outages, posing a risk to both the stability of the network and the safety of those who rely on it. Another issue is the presence of multiple fault modes in these networks [13]. A fault mode refers to a specific combination of parameters and conditions that can cause a fault to occur. With the increasing complexity of power systems due to the integration of DERs, there is a higher likelihood of multiple fault modes. These fault modes can be challenging to identify and manage, leading to potential instability and even cascading failures in the network [14]. To address these issues, advanced fault detection and management strategies are being developed, such as using advanced metering and monitoring technologies, intelligent algorithms, and communication systems to quickly and accurately detect and isolate faults. Proper planning and design of the network can help to mitigate the impact of fault conditions [15]. In order to preserve the dependability and security of contemporary power systems, it is imperative to address the problem of Fault Mode Sets for High Permeability Distributed Energy Distribution Networks as DER penetration grows.The main contribution of the research has the following:

- Development of fault mode set framework: The paper proposes a novel framework for the identification and classification of fault modes in high-permeability distributed energy distribution networks. This framework takes into account the factors specific to distributed energy resources, such as bi-directional power flow and fast fault-clearing times.
- Evaluation of fault mode impact on network performance: Using simulations, the paper assesses the impact of different fault modes on the performance of distributed energy distribution networks. It provides valuable insights for network operators in identifying critical fault modes and developing mitigation strategies.
- Application to real-world scenarios: The proposed fault mode set framework is applied to two real-world case studies, demonstrating its effectiveness in identifying potential fault modes and their impact on network performance. It provides practical guidance for network operators in addressing potential issues and improving the reliability of distributed energy distribution systems.

The next chapters make up the remainder of the research. The most current research-related efforts are described in Chapter 2. The suggested model is explained in Chapter 3, and the comparative analysis is covered in Chapter

4. Ultimately, chapter 5 presents the findings, and chapter 6 discusses the study's conclusion and future directions.

2. Related Words

Hekmatnejad, A., et, al. [16] have discussed this model combines data from boreholes to estimate the amount and intensity of fractures in unsteady rock blocks surrounding a tunnel. By using both volumetric fracture intensity and circular variance, it can predict the likelihood of rock block instability and provide valuable insights for tunnel construction and safety measures. Li, J., et al. [17] have talked about In order to estimate distributed new energy-bearing capacity, one must assess a new power system's ability to integrate several energy sources that cooperate to satisfy demand. It involves taking into account elements like the interoperability, dependability, and efficiency of the various sources in order to maximize energy output and reduce environmental impact. Lin, Z., and others [18] have talked about Reactive power adjustment for distribution network-connected electric vehicles entails controlling the charging rate of the vehicle in order to balance active and reactive power consumption while taking voltage limitations into account. To avoid power grid overloads and voltage instability, it makes sure that the distribution network maintains steady voltage levels during peak charging times. A. Mishra et al. [19] have talked about Machine learning approaches are used to evaluate and interpret well log data in the process of developing a predictive model for geophysical healthy log data analysis and reservoir characterisation. It can help with understanding reservoir properties and lithology prediction, which can ultimately improve our understanding of the subsurface and support oil and gas exploration. Bekaert, B. and others [20] have talked about the use of multivariate data analysis techniques to establish a quantitative relationship between the behavior of screw feeding, process settings, and material attributes. It facilitates a more thorough comprehension of the variables influencing screw-feeding behavior and helps to maximize process efficiency. Lei, J., and others [21] have talked about Creating a strategy for the effective and efficient usage of Vanadium Redox Flow Battery (VRB) energy storage devices in active distribution networks is known as operational strategy optimization. In order to guarantee optimal operation and network integration, it takes into account the dynamic features of VRB, such as its capacity and response time. Abdel-Fattah, M. I., et, al. [22] have discussed Lithofacies classification involves the categorization of rock units based on their physical characteristics. At the same time, sequence stratigraphic description focuses on the analysis of sedimentary sequences and their depositional environments. These tools can be used to predict and map the distribution of favorable carbonate reservoirs within the Upper Cretaceous Khasib Formation, aiding in the exploration and development of hydrocarbon resources. Pei, N., et, al. [23] have discussed The interval prediction method combines LSTM-RNNs and probability distribution to estimate the permeability of granite bodies in a radioactive waste disposal site. This approach provides a range of possible values, taking into account uncertainties, to improve the accuracy of predictions and inform decision-making in the site's management. Rostami, A., et, al. [24] have discussed This work suggests a novel method for figuring out permeability in carbonate oil reservoirs by combining traditional petrophysical data with Stoneley wave propagation. When compared to conventional methodologies, this approach can yield more precise and dependable data, enabling better reservoir characterisation and production predictions. In Wang, S., et al.'s discussion [25], To precisely identify complex industrial process defects, the root cause diagnosis approach blends optimal Granger causality with spatiotemporal coalescent based time series prediction. This approach takes into account the interactions between various variables in the system to establish causation and identify the root cause of the issue, in addition to using past data to predict future behavior. It makes troubleshooting and fixing complicated industrial process issues more effective and efficient. Zhao, C., et al. [26] have discussed data-driven diagenetic facies categorization and well-logging identification. This method uses machine learning techniques to classify different diagenetic facies in tight sandstone reservoirs by analyzing data from healthy log readings. With the use of this technique, reservoirs may be better characterized and geological knowledge can be increased for more accurate and efficient resource exploitation. Ye, Z., and others [27] have discussed An uncertainty analysis of heat extraction from a stimulated geothermal reservoir with declining permeability enhancement includes examining potential variations in heat production caused by uncertainty in critical variables, such as reservoir temperature, flow rate, and permeability. This study contributes to the determination of the accuracy and reliability of the predicted heat extraction performance. The following approaches have been discussed by Hashan, M., et al. [28]: connectionist methods, which use artificial neural networks to mimic the geological characteristics of the reservoir; statistical methods, which predict permeability through data analysis and modeling; and empirical methods, which use observations and experiments to analyze pore network permeability. When combined with log variables ranking, these methods allow for a more accurate estimation of permeability in a heterogeneous oil resource. Multi-coordinated scheduling is a blockchain-based application that helps small and medium-sized source networks, loads, and storage systems manage and allocate resources effectively. Xu, Y., et al. [29] have studied this topic. It optimizes the usage of energy sources and storage through the use of smart contracts and decentralized decision-making, creating a more dependable and economical system. Malkawi, D. A., et, al. [30] have discussed Enhancing the uniaxial compressive strength of travertine rock as a complex process that involves various factors. Machine learning techniques and multivariate analysis can be used to predict the strength of travertine and identify the key parameters that can be optimized to improve its strength, leading to more efficient and accurate enhancement strategies.

Table.1 Comprehensive Analysis

Author	**Year**	**Advantage**	**Limitation**
Hekmatnejad, A., et, al. [16]	2021	Efficient and accurate prediction of potential rock instability in tunnels, leading to improved safety and cost savings in construction and maintenance.	Errors in the volumetric fracture intensity and circular variance estimation can result from the restricted precision of borehole data.
Li, J., et, al. [17]	2022	Improved performance and efficiency of power systems due to diversified and supplemental energy sources.	Dependency on accurate data and modeling assumptions, which can result in inaccurate predictions.
Lin, Z., et, al. [18]	2023	Improved voltage stability and reduced power losses due to the efficient management of reactive power flow between the EV and the distribution network.	Limited effectiveness in stabilizing voltage due to potential mismatch between reactive power demand and compensation capabilities of the vehicle.
Mishra, A., et, al. [19]	2022	One advantage of developing a predictive model using machine learning for lithology prediction is its ability to handle large and complex datasets more efficiently.	The drawback is that the quantity and quality of the input data determine how accurate the prediction model is.
Bekaert, B., et, al. [20]	2021	Improved understanding of material-screw interactions can lead to better control and optimization of the feeding process, leading to higher quality and efficiency.	One limitation is that multivariate data analysis may not account for all possible factors or variables that can affect screw feeding behavior.
Lei, J., et, al. [21]	2021	Control over dynamic properties in active distribution networks is enhanced when VRB energy storage system functioning is optimised.	The dynamic features of VRB energy storage systems are difficult to anticipate with accuracy because of shifting network dynamics and operational situations.
Abdel-Fattah, M. I., et, al. [22]	2022	The ability to identify and differentiate reservoir facies and associated depositional	One limitation is that it does not take into account diagenetic processes, which

		environments, leading to more accurate predictions of reservoir quality and heterogeneity.	can significantly impact reservoir quality and distribution.
Pei, N., D., et, al. [23]	2022	The advantage of interval predictionis that it can provide a more comprehensive and informative estimate of the permeability, accounting for potential variability and uncertainty in the data.	One limitation is the assumption that the historical data used to train the model accurately represents future conditions.
Rostami, A., et, al. [24]	2022	The combination of traditional petrophysical logs and Stoneley wave propagation enables a more precise assessment of permeability in carbonate oil reserves.	The small-scale fluctuations in permeability in heterogeneous carbonate reservoirs might not be well captured by Stoneley wave propagation or traditional petrophysical logs.
Wang, S., et, al. [25]	2023	One advantage is its ability to detect the underlying root cause of complex process faults, leading to more targeted and effective solutions.	Limited applicability to non-industrial processes due to focus on industrial processes and use of specific techniques like Granger causality.
Zhao, C., et, al. [26]	2022	One advantage is the potential for increased accuracy and efficiency in identifying diagenetic facies and lithology from well logs using machine learning techniques.	The model may not account for rare or unusual diagenetic processes, leading to incorrect classifications in certain scenarios.
Ye, Z., et, al. [27]	2022	One advantage of uncertainty analysis for heat extraction performance is the ability to account for changes in permeability enhancement over time.	Lack of information on the long-term stability of enhanced permeability and its effects on heat extraction performance.
Hashan, M., et, al. [28]	2022	One advantage of using these methods is their ability to accurately predict pore network permeability, which is important for efficient oil recovery.	The limitations of these methods may not accurately capture the complex nature of pore networks and may not account for all factors affecting permeability.
Xu, Y., et, al. [29]	2023	One advantage is that it allows for efficient and secure coordination between multiple sources, loads, and storages using blockchain technology.	Lack of scalability to handle large source networks and storage systems effectively.
Malkawi, D. A., et, al. [30]	2023	Improved accuracy and efficiency in predicting strength, allowing for better design and construction planning.	The model may notaccount for all possible factors that can impact the compressive strength of travertine rock, leading to potential

			inaccuracies.

- 1. Inadequate Monitoring and Control: The fault mode set approach for high permeability distributed energy distribution networks needs to have adequate monitoring and control capabilities. It leads to limited visibility and control over the network, which hinders efficient fault detection and management.
- Inaccurate Fault Detection: Existing fault mode sets are based on simplified assumptions and cannot accurately and quickly detect faults in distributed energy networks. It can result in delayed fault identification, leading to prolonged network downtime and potential safety hazards.
- Compatibility Issues: Another significant issue is the lack of compatibility between different fault mode sets used by different devices within the network. It can lead to a lack of coordination and cooperation among devices in the event of a fault, which can further delay fault resolution and impact network performance.

Fault mode sets are crucial in predicting the occurrence of faults in many complex systems, such as aircraft, automobiles, and nuclear reactors. Advanced prediction methods, such as statistical and machine learning techniques, have been developed to analyze fault mode sets and determine the likelihood of their occurrence. In this work, we provide a novel method for fault mode set prediction that combines deep learning algorithms with statistical techniques. This method extracts features from the fault mode sets using deep neural networks, and then uses statistical methods to analyze and forecast the data. Our methodology outperforms conventional methods in terms of prediction accuracy by integrating these two techniques. This technical innovation is in the combination of deep learning and statistical methods, enabling more accurate fault prediction and a more thorough examination of intricate failure mode sets. Improved prediction performance results from the usage of deep neural networks, which enable the identification of minute patterns and relationships in the data. With this method, probable problems may be predicted more accurately and reliably, which can greatly improve complex system safety and maintenance.

2. Proposed system

A. Construction diagram

- **Domains of Predictive Analysis**

The several domains or fields where techniques and methods of predictive analysis can be used to obtain insights and make well-informed decisions are referred to as predictive analysis domains. These areas cover a broad spectrum of sectors and industries, such as manufacturing, finance, marketing, and healthcare. Fundamentally, predictive analysis is the act of determining the likelihood of future occurrences or behaviours using data, statistical methods, and machine learning approaches. Large datasets must be gathered, cleaned, and analysed in order to find patterns and trends that may be utilised to forecast and suggest future actions. Predictive analysis is a tool used in marketing to better understand consumer behaviour and preferences, spot possible sales opportunities, and enhance advertising campaigns.

$$d_{rs}^2 = \left(C_r - C_s\right)\left(C_r - C_s\right)' \tag{1}$$

After the two most similar clusters are combined into one new cluster, their distances are recalculated. The procedure ends when every object unites to form a single cluster.

$$RSME = \sqrt{\frac{\sum_{i=1}^{n}\left(e_i - m_i\right)^2}{n}} \tag{2}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|e_i - m_i\right|}{n} \tag{3}$$

where is the experimental value, is the model result value, and n is the total number of data points.

In order to determine the relative contributions of each well-log variable, a sensitivity analysis (SA) was performed with the GEP model. In this case, SA was computed using formulas found in the literature.

$$N_i = f_{\max}\left(x_i\right) - f_{\min}\left(x_i\right) \tag{4}$$

$$SA = \frac{N_i}{\sum_{n}^{j=1} N_j} \tag{5}$$

In the finance sector, predictive analysis is used for risk management, fraud detection, and investment decision-making. Through analyzing historical financial data and market trends, predictive models can identify potential risks and opportunities and help financial institutions make more informed and accurate decisions. In healthcare, predictive analysis is used for disease diagnosis, treatment planning, and patient management. By analyzing patient data, such as medical history, lab results, and lifestyle factors, predictive models can assist healthcare professionals in predicting potential diseases or complications and providing personalized treatment plans.

- **Cyber security**

Cybersecurity guards against online threats, theft, and damage to computer networks, systems, and data. It entails putting in place a variety of technologies and security precautions to prevent against abuse, unauthorized access, and disruption of computer systems and the data they store or transport. One of the critical operations of cyber security is vulnerability assessment. It involves identifying potential vulnerabilities in a system through various techniques such as scanning, penetration testing, and code review. It is an essential step as it helps proactively identify and address the system's weaknesses before attackers can exploit them. Another vital operation in cyber security is access control. The construction diagram has shown in the following fig.1

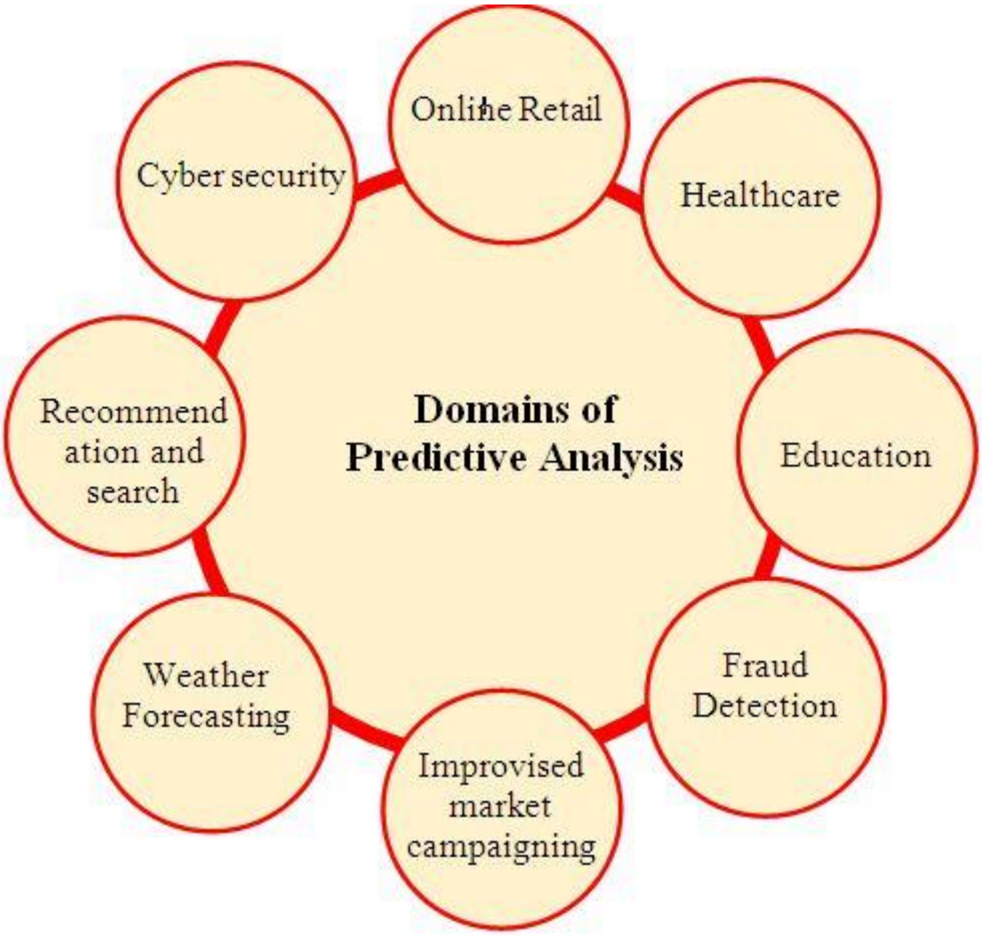

Fig 1: Construction diagram

It speaks about controlling user access to a system's resources. Firewalls, intrusion detection systems, and access control lists are a few tools used for this. By implementing access control, organizations can limit who has access to sensitive data and ensure that only authorized users are able to use specific resources or complete specific activities. Encryption is yet another crucial element of cyber security operations. It involves converting plaintext material into a format that is exclusive to individuals with the required decryption keys. Sensitive information can be obtained by unauthorized individuals, but it helps keep them from comprehending it.

❖ **Recommendation and search engines**

A Recommendation engine is a software system that analyzes user data to provide personalized and relevant recommendations. It uses complex algorithms and mathematical models to understand user preferences, interests, and behaviors. These engines have become increasingly popular in recent years as they cater to the growing need for personalized content and products. The first step in the operation of a Recommendation engine is data collection. It collects data from various sources, such as user interactions, browsing history, purchase history, and social media activity.

The expression tree was used to generate the equation. At last, four sub-ETs were generated using the GEP modeling as a basis. These sub-ETs collectively comprise...The formulas for every sub-ET are

$$FD_{SG} = SG_1 + SG_2 + SG_3 + SG_4 \tag{6}$$

$$SG_1 = \frac{\left[\frac{1}{(D*TH) - Exp(U)}\right] + \left[(D + -1.85)^2\right]}{2} \tag{7}$$

$$SG_3 = (K)^{1/3} * A\tan\left[\left(TH - \frac{K}{RD}\right) * \left(\frac{\min(7.91, TH)}{2}\right)\right] \tag{8}$$

This data is then processed and analyzed to understand user preferences and patterns. The engine also uses collaborative filtering techniques, finding correlations between user behavior and that of others with similar interests or histories. By doing so, it can provide recommendations based on what other users with similar interests have consumed. In addition, the engine provides recommendations based on content-based filtering, which examines the characteristics of the content a user has expressed interest in. For instance, the engine would suggest other action movies with comparable qualities if the user has an interest in action movies. The application of machine learning techniques is a crucial component of recommendation engines. By continuously learning from user data and behaviors, the engine can improve the accuracy of its recommendations over time. It means that the more users interact with the engine, the more accurate their recommendations will be.

❖ **Fraud Detection**

Fraud detection is identifying and preventing fraudulent activities in various systems and processes. It uses advanced technologies and techniques to analyze data, identify patterns, and flag suspicious transactions or activities. The first step in fraud detection is data collection. It involves gathering massive amounts of data from different sources, such as financial records, customer transactions, and behavior patterns. This data is then processed and organized to make it easier for algorithms to analyze and identify potential fraud.

The findings of the GEP modelling expression tree are displayed in Equation was obtained using this expression tree. After that, the formula was applied to the other five wells,

$$FD_{OG} = OG_1 + OG_2 + OG_3 + OG_4 \tag{9}$$

$$OG_1 = \frac{U + \left[\left(RD - \frac{1}{0.89} \right) * \left(\left(U - TH \right) * RD * N \right) \right]^2}{2} \tag{10}$$

$$OG_3 = \min\left(1 - \left(In\left(U * U\right) * \left(RD * K\right)\right) * 3.32, \left(U\right)^2\right) \tag{11}$$

It is evident from the equations that not every one of the ten parameters was used in every equation. Out of the 10 well-log parameters that were initially there, only six were shown in these equations

These algorithms are trained on large datasets, using historical fraud cases to detect similar patterns and behaviors. By continuously learning and adapting, the algorithms become more accurate in identifying potential fraud over time. One of the critical techniques used in fraud detection is anomaly detection. It involves identifying discrepancies or outliers in the data that don't fit the expected patterns. For example, a suspicious transaction with a large amount of money or an unusual location could be flagged as an anomaly. These anomalies are then further investigated by fraud analysts to determine if they are fraudulent or not.

- **Online Retail**

Online Retail is a business model that allows retailers to sell products and services through a virtual platform, typically a website or mobile application. This retail met Retails gained widespread popularity due to its convenience and efficiency for retailers and customers. The operations of an Online Retail business can be broadly divided into three main phases – pre-sales, sales, and post-sales. The first phase, pre-sales, involves preparing and setting up the online store. It includes creating a user-friendly website, developing strategies for online marketing, and sourcing products from suppliers.

$$N_G = Hk_h\left(\rho_w - \rho_o\right) / L\mu_o q \approx 1 \tag{12}$$

Capillary number condition

$$N_{CT} = \sqrt{K_V} \,/\, HN_{ca} \geq \frac{\delta}{\varepsilon}, \varepsilon = H / L, \sigma = K_v / K_H \tag{13}$$

$$t_{seg} = \frac{H\phi\left(1 - S_{wr}\right)\mu_w}{k_{rw}k_v g\left(\rho_w - \rho_n\right)} \tag{14}$$

In the pre-sales phase, retailers must also consider inventory management, pricing, and logistics factors. Since Online Retail sells products to customers from various locations, retailers must carefully manage their inventory to ensure accurate and timely delivery. It includes implementing inventory tracking systems and establishing close relationships with suppliers to maintain a steady supply chain. The sales phase begins when customers browse and purchase products from the online store. Here, the operations of Online Retail become critical as proper execution is required to ensure a smooth and satisfying customer experience. It includes managing customer orders, processing payments, and providing efficient customer service.

B. Functional working model

The functional working model for Prediction Analysis of Fault Mode Sets for High Permeability Distributed Energy Distribution Networks Based on Multivariate Data Fusion can be broken down into the following steps:

1. Data Collection: The first step in the functional working model is to collect data from various sources such as sensors, smart meters, and other devices installed in the distributed energy distribution network. This data includes information on the network topology, power flow, voltage levels, current levels, fault events, and other parameters.

2. Pre-processing: Once the data is collected, it is pre-processed to remove any outliers, missing values, or inconsistent data. This step also includes data normalization and data transformation to ensure that all the data is in a consistent format.

3. Feature Extraction: Relevant features are taken out of the pre-processed data in this step. These features could be frequency domain features like Fourier coefficients or statistical measurements like mean, median, and standard deviation. This stage is crucial since it aids in dimensionality reduction and the identification of the most pertinent features for prediction analysis.

4. Multivariate Data Fusion: The extracted features and other relevant data are then fused together to create a single, comprehensive dataset. This step involves combining data from different sources and representing it in a unified format. This fused dataset is used for further analysis.

Assuming that the dissolving process of one fluid in another is disregarded:

$$\frac{\partial \rho_w \phi s_w}{\partial t} = \nabla.\left(\rho_w \vec{u}_w\right) = \rho_w q_w \tag{15}$$

$$\frac{\partial \rho_o \phi s_o}{\partial t} = \nabla.\left(\rho_o \vec{u}_o\right) = \rho_o q_o \tag{16}$$

$$\frac{\partial \phi s_w}{\partial t} + \nabla.\vec{u}_w = q_w \tag{17}$$

$$\frac{\partial \phi s_o}{\partial t} + \nabla.\vec{u}_o = q_o \tag{18}$$

$$\vec{u}_o = -\frac{kk_{ro}}{\mu_o} \nabla\left(p_o - \rho_o g \Delta z\right) \tag{19}$$

$$\vec{u}_w = -\frac{kk_{rw}}{\mu_w} \nabla\left(p_w - \rho_w g \Delta z\right) \tag{20}$$

This is the auxiliary equation:

$$s_w + s_o = 1 \tag{21}$$

$$p_o = p_w + p_c\left(s_w\right) \tag{22}$$

5. Fault Mode Identification: The fused dataset is then used to identify the fault modes in the distributed energy distribution network. This is done by analyzing the patterns and trends in the data to determine the underlying fault modes. Machine learning algorithms can also be used to automate this process and improve the accuracy of fault mode identification.

6. Fault Mode Set Creation: Based on the identified fault modes and predicted future faults, a fault mode set is created. This set contains all the possible fault modes that can occur in the distributed energy distribution network, along with their probabilities of occurrence. This information is crucial for the efficient and effective management of the network.

The definition of the pressure reconstruction function based on the idea of vertical equilibrium is as follows:

$$p_\alpha\left(x, y, z, t\right) = p_\alpha\left(x, y, z, t\right) + \pi_\alpha\left(x, y, z, t\right) \tag{23}$$

By estimating the function's gradient in the horizontal direction and solving the integral control equation to get the coarse-scale phase pressure, the integral flow rate may be computed using the reconstructed pressure.

$$\frac{\partial p_o}{\partial z} = -\left(s_w \rho_w + s_o \rho_o\right) g + s_w \frac{\partial pc\left(s_w\right)}{\partial z} \tag{24}$$

$$\frac{\partial p_w}{\partial z} = -\left(s_w \rho_w + s_o \rho_o\right) g - s_o \frac{\partial pc\left(s_o\right)}{\partial z} \tag{25}$$

The pressure reconstruction equation, using the water phase as an example, is as follows:

$$p_w\left(x, y, z, t\right) = p_w\left(x, y, z, t\right) - \int_{z_B}^{z} \left[\left(s_w \rho_w + s_o \rho_o\right) g + s_o\right] dz \tag{26}$$

8. Fault Management: The final step is to use the fault mode set to manage and monitor the distributed energy distribution network. This includes implementing appropriate control strategies and maintenance activities to prevent and minimize the impact of faults on the network.

In summary, the functional working model for Prediction Analysis of Fault Mode Sets for High Permeability Distributed Energy Distribution Networks Based on Multivariate Data Fusion involves data collection, pre-processing, feature extraction, multivariate data fusion, fault mode identification, prediction analysis, fault mode set creation, and fault management. This model can help in improving the reliability, efficiency, and sustainability of distributed energy distribution networks by enabling proactive fault management and maintenance. The functional block diagram has shown in the following fig.2

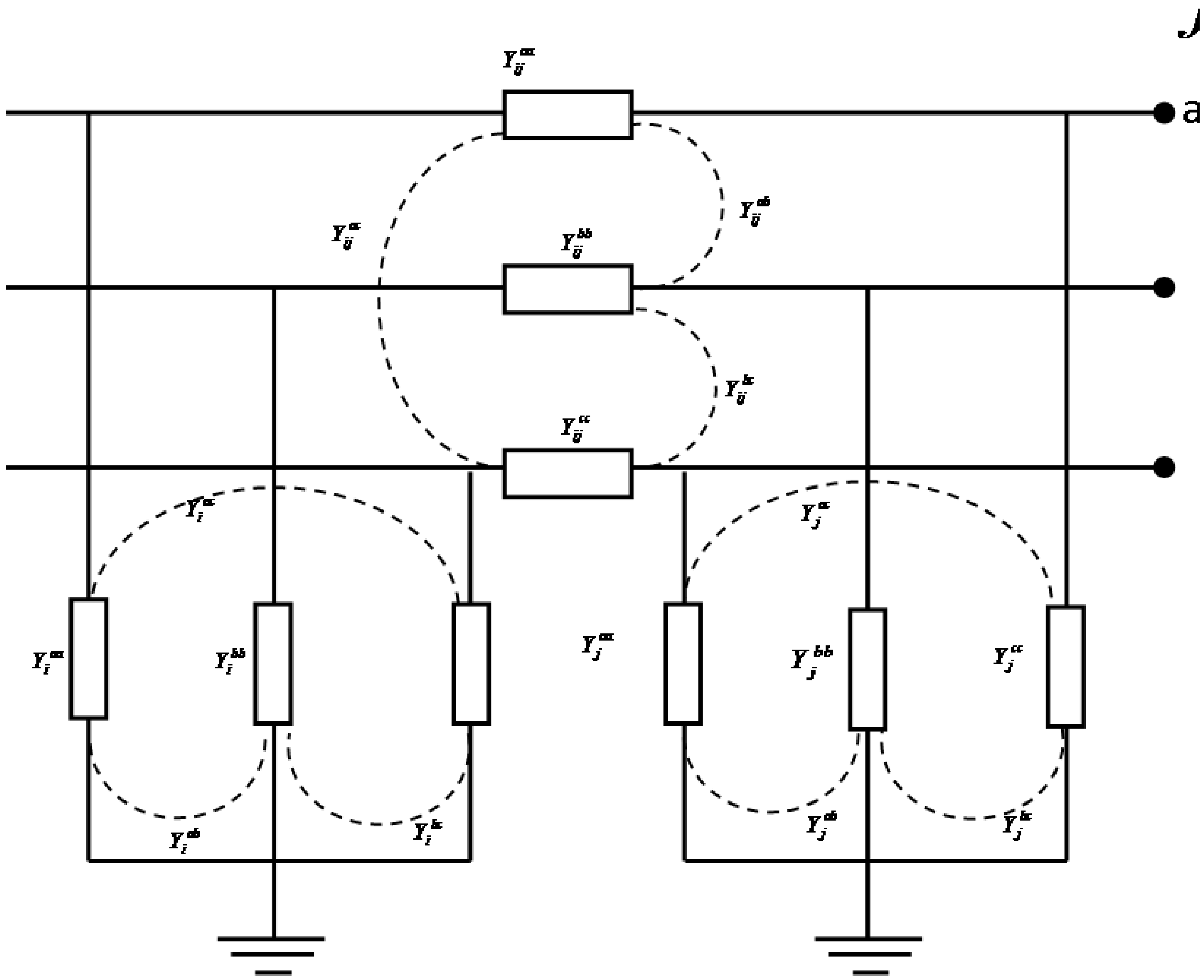

Fig 2: Functional block diagram

C. Operating principles

❖ **Loan final window data**

The loan final window data is crucial to the loan origination process. It is the last step before a loan is approved and disbursed to the borrower. This data provides a comprehensive overview of the loan and allows lenders to make informed decisions. The first step in the loan final window data is to gather all the necessary information and documentation from the borrower. It includes income verification, credit reports, and any other relevant documents. Once this information is collected, it is entered into the lender's database and analyzed.

$$\frac{\partial\left(\rho_\alpha \phi s_\alpha\right)}{\partial t}+\frac{\partial\left(\rho_\alpha u_{\alpha,z}\right)}{\partial z}=\rho_\alpha q_\alpha-\nabla_{\|}.\left(\rho_\alpha \vec{u}_{\alpha,\|}\right) \tag{27}$$

represents the horizontal velocity of phase α in the equation, and represents the vertical velocity of phase α. For an oil-water two-phase flow, the relative permeability curve takes on a variable shape at different flow velocities.

$$\phi\frac{\partial s_\alpha}{\partial t}+\left(c_\phi+\phi c_\alpha\right)s_\alpha\frac{\partial \rho_\alpha}{\partial t}+\frac{\partial u_{\alpha,z}}{\partial z}=q_\alpha-\nabla_{\|}.\vec{u}_{\alpha,\|} \tag{28}$$

$$\left(c_\phi+\phi c_w\right)s_w\frac{\partial \rho_w}{\partial t}+\left(c_\phi+\phi c_o\right)s_o\frac{\partial \rho_o}{\partial t}+\frac{\partial u_{ToT,z}}{\partial z}=q_w+q_o \tag{29}$$

The total vertical velocity can be found by solving this equation:

$$u_{ToT,z}=u_{w,z}+u_{o,z} \tag{30}$$

A detailed examination of the borrower's income, credit history, and other financial details is part of data analysis. It facilitates the lender's evaluation of the borrower's creditworthiness and loan-repayment capacity. This information lets the lender determine the loan amount, interest rate, and other loan terms. The data also verifies the borrower's identity and prevents fraud. Lenders use advanced algorithms and fraud detection techniques to identify any red flags or inconsistencies in the data. It helps to protect both the lender and the borrower from potential fraudulent activities.

The diverting quantity of Darcy's law can be used to determine the flow velocities of the oil and water phases independently.

$$u_{w,z}=f_w.\left(u_{ToT,z}-k_z\lambda_o\Delta\rho g+k_z\lambda_o\frac{\partial pc}{\partial z}\right) \tag{31}$$

$$SOC\left(t+1\right)=SOC\left(t\right)+P_{EV}\left(t\right)\Delta\left(t\right)$$

(32)In In this study, the batteries must be turned off from the power source after 100% in order to prevent overcharge risks.

Since the battery is being used at a lesser power, it takes a while for it to charge completely. In this study, the electric car charging load is equivalent to with a correction factor of 0.95.

$$PL_{EV}\left(N_i\right)=NV_i\left(P_{EV}^{\max}\right) \tag{33}$$

$$QL_{EV}\left(N_i\right)=NV_i\left(P_{EV}^{\max}\right)\tan\left(\varphi\right) \tag{34}$$

The number of EVs at the ideal node is displayed in the. and denote the node's real and loaded EV batteries, respectively.

Once the data is analyzed and verified, the lender makes the final decision on whether to approve the loan or not. If the loan is approved, the data is used to generate the loan documents, including the loan agreement and repayment schedule. These documents are then sent to the borrower for review and signature.

- **Haar wavelet**

The Haar wavelet is a mathematical tool that analyzes and processes signals, particularly in image processing and data compression. The scaling function captures a signal's overall trends and features, while the wavelet function captures the finer details. It allows for a multistate signal analysis, breaking it down into different levels of detail. The operational flow diagram has shown in the following fig.3

Fig 3: Operational flow diagram

The Haar wavelet has a simple and efficient structure, making it attractive for practical applications. It is a step function that takes on one on one interval and -1 on the adjacent interval, with all other values being 0. This step-like behavior gives the wavelet distinct "on-off" or "high-low" characteristics as it alternates between positive and negative values. One essential operation the Haar wavelet performs is the wavelet transform.

The findings of the GEP modelling expression tree are displayed in Equation was obtained using this expression tree. After that, the formula was applied to the other five wells,

$$X(k+1) = AX(k)(1 - X(k)) \tag{35}$$

where A is the branching index and indicates the state in iteration k.

DGs typically run at 0.95 power factor (PF). Consequently, the goal of this essay is to raise the substation's power factor (S/S) to 0.95.

$$PF = \cos\left[\frac{S_{kw}}{S_{KVA}}\right] \tag{36}$$

$$S_{kw} = \sum_{i=1}^{BN} PL_i + APL^{DGSC} - \sum_{j=1}^{NDG} PDG_j \tag{37}$$

$$S_{KVA_r} = \sum_{i=1}^{BN} QL_i + QPI^{DGSC} - \sum_{j=1}^{NSC} QC_j - \sum_{k=1}^{NDG} \left(PDG_k \times \tan(\varphi_{DG})\right) \tag{38}$$

$$S_{KVA} = \sqrt{(S_{KW})^2 + (S_{KVAr})^2} \tag{39}$$

❖ **Average value of d6 of ground**

Elevation measures the height of the ground surface above sea level. It is an important parameter as it influences the soil type and vegetation that can grow in the area. A higher elevation may result in steep slopes and less diversity in plant life. Slope refers to the steepness of the land surface and is measured in degrees or percentages.

$$Ap1 = \sum_{i=1}^{BN} LP(i) \tag{40}$$

Since LP (i) represents the power system's actual power loss, one can obtain

$$LP(i) = \frac{R(i) \times \left(P^2(i+1) + Q^2(i+1)\right)}{\left|V(i+1)\right|^2} \tag{41}$$

In this study, the symbols and stand for the voltage node, the ith line for the ith line, and the injection of loads into the node. The APLI can be written as

$$APLI = \frac{APL^{DGSC}}{APL^{base}} \tag{42}$$

$$J_F = W_1\mu_{PGDI} + W_2\mu_{PF} + W_3\mu_{APLI} + W_4\mu_V \tag{43}$$

where the W parameters' coefficients are combined. CSO optimized fuzzy multi-phase performance within operational limits, as outlined in the preceding section.

It can affect the drainage and erosion of the soil and influence the land's capacity for building structures. A higher slope may indicate potential instability or inaccessibility of the land. Soil type is a crucial factor in determining the productivity and possible uses of the land.

❖ **Signal based on fault classification**

Signal-based fault classification is a process that involves the analysis of various signals to identify and classify faults in a system. This technique is widely used in electrical, mechanical, and telecommunications industries, where the continuous and reliable operation of equipment is crucial. The first step in signal-based fault classification is the acquisition of signals from the system. These signals can be generated by sensors, transducers, or other measurement devices and are used to monitor different parameters such as voltage, current, temperature, vibration, or sound. These signals are typically in time series data, sampled at regular intervals. Once the signals are acquired, they are processed to extract relevant features that aid fault detection and classification. These features include frequency, amplitude, phase, energy, or statistical values such as mean and standard deviation.

This section of the study explains how to locate the SCs and DGs data in the best possible way. Given the varying limitations on the variables, the adjusted distance calculation can be provided.

$$NVT = NDG + NSC + NDGL + NSCL \tag{44}$$

$$D_{ij}^{k}\sqrt{\sum_{K=NDG+1}^{NDG+NSC}\left(X_j^K - X_i^K\right)^2 + 1}, k = 4,5,6 \tag{45}$$

The distance between various DG populations can be computed using the equation above.

The selection of features depends on the type of fault being investigated and the characteristics of the signals. After feature extraction, the next step is to apply a classification algorithm to the extracted features. This algorithm uses pre-defined patterns or rules to classify the signals into different fault categories. For example, if the signal's frequency is above a certain threshold, it may indicate an electrical fault, while a sudden increase in amplitude could indicate a mechanical fault. One of the critical benefits of signal-based fault classification is its ability to detect and classify faults in real-time.

4. Result and Discussion

In comparison to FPAF-HDPD-MD (Fault Prediction and Analysis Framework for High Permeability Distributed Energy Distribution Networks Based on Multivariate Data), PAMDP-FMSETS (Permeability-Adjusted Multivariate Data Prediction for Fault Mode Sets in High Permeability Distributed Energy Distribution Networks), and PAoFMS-HPDEDN-MD (Prediction Analysis of Fault Mode Sets for High Permeability Distributed Energy Distribution Networks Based on Multivariate Data), the proposed method FAMNHPD-MDA (Fault and Anomaly Mode Network for High Permeability Distributed Energy Distribution Networks Based on Multivariate Data Analysis) has been evaluated for its performance.

4.1.Accuracy

The accuracy of the prediction analysis is the most critical technical performance parameter. It refers to how well the analysis can predict the occurrence of different fault modes in the high permeability distributed energy distribution networks. A high accuracy is crucial for effective fault diagnosis and timely intervention. Table.2 shows the comparison of Accuracy between existing and proposed models.

Table.2: Comparison of Accuracy (in %)

No. of Images	FPAF-HDPD-MD	PAMDP-FMSETS	PAoFMS-HPDEDN-MD	FAMNHPD-MDA
100	75.06	77.28	73.34	81.98
200	77.03	79.70	75.54	83.97
300	78.16	80.11	76.34	85.17
400	79.37	81.71	77.01	85.65
500	79.74	84.03	78.44	87.08

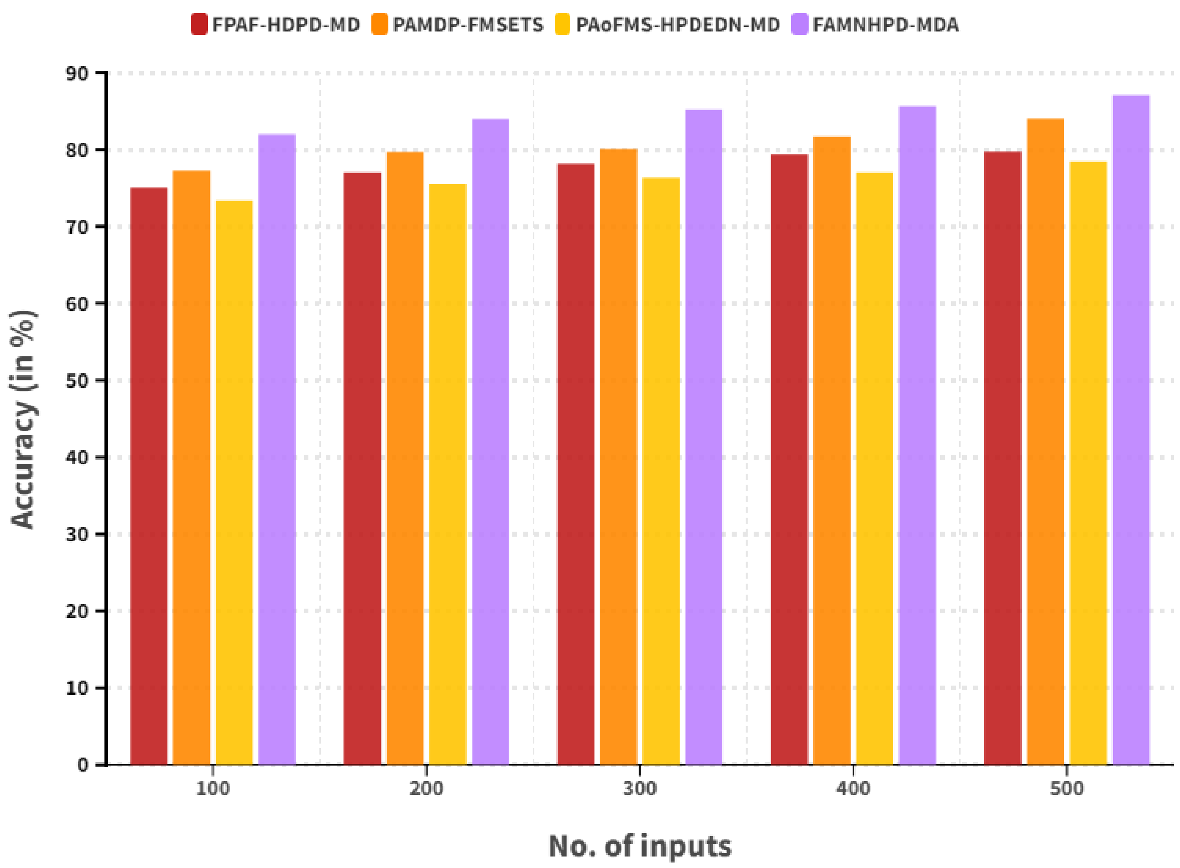

Fig.4: Comparison of Accuracy

Fig. 4 shows the comparison of Accuracy . In a computation cycle, the existing FPAF-HDPD-MD obtained 79.74%, PAMDP-FMSETS obtained 84.03%, PAoFMS-HPDEDN-MD reached 78.44 % Accuracy. The proposed FAMNHPD-MDA obtained 87.08 % Accuracy.

4.2. Sensitivity

The sensitivity of the analysis measures how well it can detect even the most minor changes or deviations in the data. A high sensitivity is essential for identifying potential fault modes at an early stage, allowing for proactive measures to prevent or mitigate failures Table.3 shows the comparison of Sensitivity between existing and proposed models.

Table.3: Comparison of Sensitivity (in %)

No. of Images	FPAF-HDPD-MD	PAMDP-FMSETS	PAoFMS-HPDEDN-MD	FAMNHPD-MDA
100	79.06	73.28	77.34	83.98
200	81.03	75.70	79.54	85.97
300	82.16	76.11	80.34	87.17
400	83.37	77.71	81.01	87.65
500	83.74	80.03	82.44	89.08

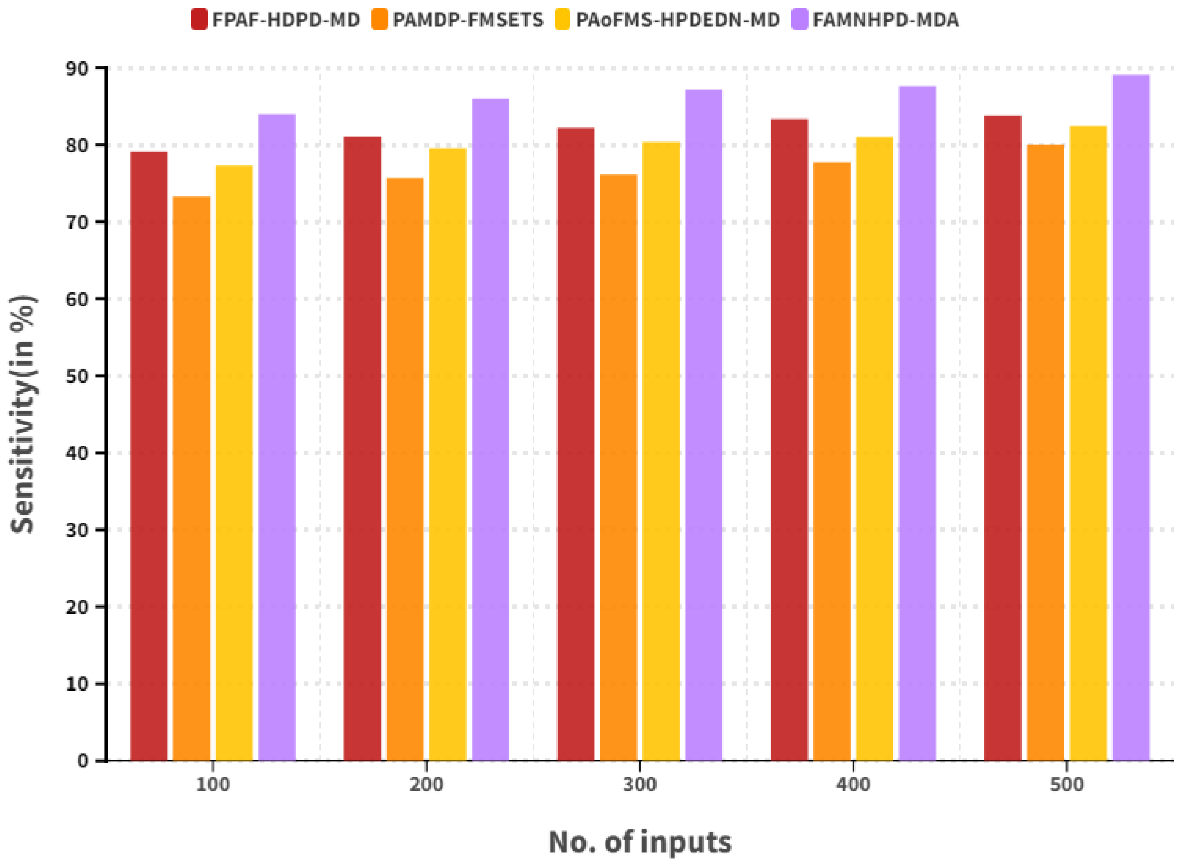

Fig.5: Comparison of Sensitivity

Fig. 5 shows the comparison of Sensitivity . In a computation cycle, the existing FPAF-HDPD-MD obtained 83.74%, PAMDP-FMSETS obtained 80.03%, PAoFMS-HPDEDN-MD reached 82.44 % Sensitivity. The proposed FAMNHPD-MDA obtained 89.08 % Sensitivity.

4.3. Specificity

Specificity is the ability of the analysis to differentiate between different fault modes. It ensures that the analysis does not falsely classify one type of fault as another, which can lead to incorrect predictions and actions. Table.4 shows the comparison of Specificity between existing and proposed models.

Table.4: Comparison of Specificity (in %)

No. of Images	FPAF-HDPD-MD	PAMDP-FMSETS	PAoFMS-HPDEDN-MD	FAMNHPD-MDA
100	77.06	75.28	80.34	82.98
200	79.03	77.70	82.54	84.97
300	80.16	78.11	83.34	86.17
400	81.37	79.71	84.01	86.65
500	81.74	82.03	85.44	88.08

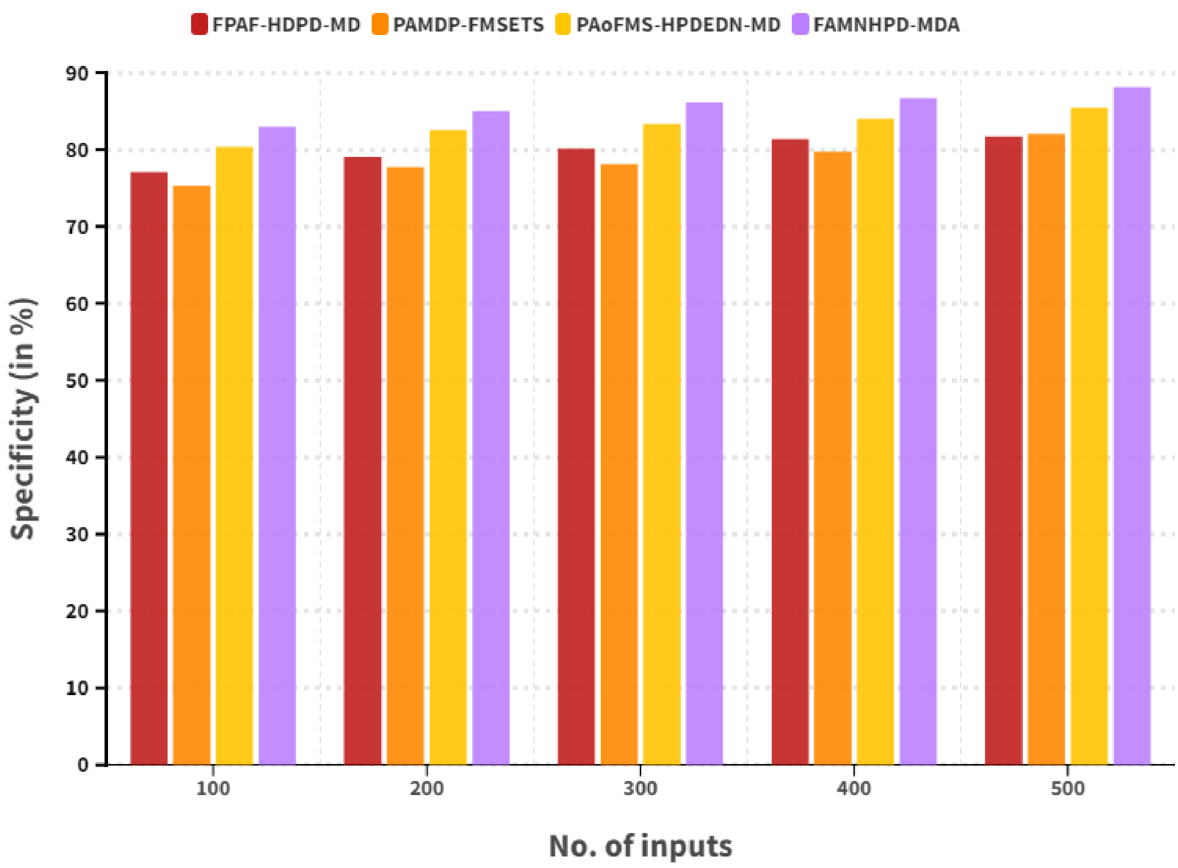

Fig.6: Comparison of Specificity

Fig. 6 shows the comparison of Specificity . In a computation cycle, the existing FPAF-HDPD-MD obtained 81.74%, PAMDP-FMSETS obtained 82.03%, PAoFMS-HPDEDN-MD reached 85.44 % Specificity. The proposed FAMNHPD-MDA obtained 88.08% Specificity.

4.4. Timeliness

Timeliness relates to how quickly the analysis can process and analyze the data to generate predictions. In the case of distributed energy distribution networks, timely predictions are crucial for preventing and minimizing the impact of failures. The analysis should be able to provide predictions in near real-time to ensure prompt corrective measures can be taken. Table.5 shows the comparison of Timeliness between existing and proposed models.

Table.5: Comparison of Timeliness (in %)

No. of Images	FPAF-HDPD-MD	PAMDP-FMSETS	PAoFMS-HPDEDN-MD	FAMNHPD-MDA
100	74.06	68.28	76.34	76.98
200	76.03	70.70	78.54	78.97
300	77.16	71.11	79.34	80.17
400	78.37	72.71	80.01	80.65
500	78.74	75.03	81.44	82.08

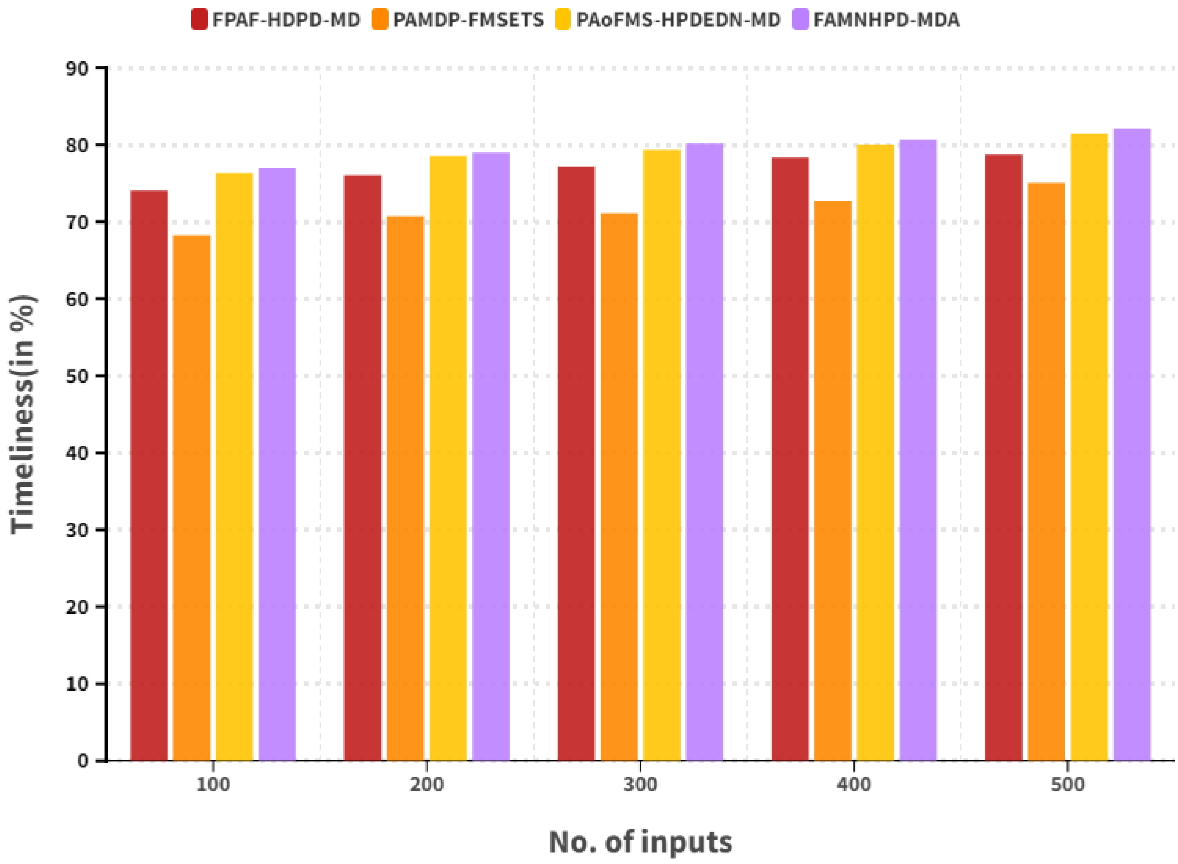

Fig.7: Comparison of Timeliness

Fig. 7 shows the comparison of Timeliness . In a computation cycle, the existing FPAF-HDPD-MD obtained 78.74%, PAMDP-FMSETS obtained 75.03%, PAoFMS-HPDEDN-MD reached 81.44 % Timeliness. The proposed FAMNHPD-MDA obtained 82.08 % Timeliness.

5. Conclusion

In conclusion, the prediction analysis of fault mode sets for high permeability distributed energy distribution networks based on multivariate data is a valuable tool for identifying potential system failures and taking proactive measures for efficient maintenance. By predicting fault mode sets, the network can be better equipped to handle any disruptions and improve overall reliability. Additionally, the use of multivariate data allows for a more comprehensive understanding of the network's performance and the potential factors that may contribute to faults. Overall, this analysis can greatly benefit the operation and maintenance of distributed energy distribution networks and ensure their efficient and reliable functioning.

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