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Multiple Data Sources in Reliability Assessment of Distribution Networks

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Abstract: - Since distribution networks provide the regular and secure transmission of power to consumers, its dependability is essential to the smooth operation of modern society. Conventional techniques for evaluating these networks' dependability have depended on a single data source, such as historical outage statistics. The capacity to combine many data sources into dependability evaluation has been possible due to technological improvements and the abundance of available data. This allows for a more thorough and precise understanding of network performance. This technical abstract proposes a methodology for incorporating multiple data sources in the reliability assessment of distribution networks. It is to identify and collect various data sources such as weather data, customer complaints, equipment maintenance records, and outage data. These data sources are then integrated and analyzed using statistical and machine learning algorithms to identify patterns and correlations that can provide insights into the network's reliability.

Keywords: Reliability, Assessment, Machine Learning, Customer Complaints, Equipment Maintenance, Weather Data

1. Introduction

Distribution network reliability assessment is a technical evaluation method that gauges how well a distribution network performs and how resilient it is in providing end consumers with electricity. It is a crucial component of the design and management of the power system since it guarantees a steady and dependable supply of electricity to a range of users [1]. The purpose of reliability evaluation is to pinpoint the crucial elements of the distribution network, including switches, feeders, and transformers. These elements are very prone to malfunction, and the network's dependability is directly impacted by their performance [2]. Following identification, the failure rates and durations of these components are observed. Many indicators and indices are used to evaluate the distribution network's dependability [3]. SAIDI (System Average Interruption Duration Index) and SAIFI (System Average Interruption Frequency Index) are the two most widely utilized indices. While SAIFI measures the average number of interruptions, SAIDI measures the average duration of interruptions that end users experience [4]. These indices provide a comparative analysis of the reliability of different networks and also help in identifying the areas that require improvement. Reliability assessment also takes into account the causes of failures, such as weather events, equipment malfunction, and human error [5]. By analyzing the causes of failures, the network operators can implement preventative measures to reduce the likelihood of failures and improve overall network reliability [6]. The results of reliability assessment are used to make informed decisions on network improvements and investments. It can also assist in identifying vulnerable areas and help in planning for future growth or load increases [7]. Reliability assessment of distribution networks is a crucial aspect in ensuring the efficient functioning and delivery of electricity to end-users [8]. It involves evaluating and monitoring the performance and response of distribution networks in delivering electricity and identifying any potential issues that may affect their reliability. Some of the critical

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technical issues related to the reliability assessment of distribution networks include aging infrastructure, weather-related events, and equipment failures [9]. One major issue in the reliability assessment of distribution networks is the aging infrastructure [10]. Over time, the components of distribution networks, such as power lines, transformers, and switchgear, can deteriorate due to wear and tear, corrosion, and external factors such as extreme weather conditions [11]. It can lead to increased downtime and disruptions in the electricity supply, leading to reduced reliability. It is essential to regularly inspect and maintain these components to identify any potential issues and prevent failures that can affect the reliability of the distribution network [12]. Weather-related events, such as storms, hurricanes, and extreme temperatures, are another primary concern in the reliability assessment of distribution networks [13]. These events can cause physical damage to the distribution infrastructure, leading to power outages and disruptions in the supply of electricity [14]. Severe weather events can also affect the functioning of other systems, such as communication networks and substations, further impacting the reliability of the network [15]. To address this issue, distribution network operators need to invest in technologies such as weather monitoring systems and resilient infrastructure that can withstand extreme weather conditions. The main contribution of the paper has the following,

- Improved grid stability and power quality: The reliability assessment of distribution networks helps in identifying potential failure points and areas of weak infrastructure, enabling utilities to make necessary repairs or improvements. This results in improved grid stability and power quality, thereby ensuring a more consistent and reliable supply of electricity to customers.
- Cost savings and efficient maintenance: By identifying areas with a high risk of failure and determining their impact on the overall network, utility companies can prioritize maintenance and repair activities. Cost-effective management of the distribution network.
- Better planning and grid expansion: Reliability assessment of distribution networks provides valuable information that can be used for future planning and expansion of the grid. By understanding the reliability levels of different parts of the network, utilities can identify areas that require upgrades or reinforcements, making their grid more resilient and better able to meet future demand.

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

Zhu, J., et al. [16] have talked about A mathematical optimization technique called mixed-integer linear programming (MILP) based distribution network reconfiguration model is used to increase a power distribution network's reliability. It takes into account how best to set up network elements like feeders and switches to reduce the chance of power outages and provide a more dependable and effective distribution of electricity.Digital servitization, defined as the use of digital technology to enable the conversion of traditional industrial enterprises into service-oriented ones, has been covered by Chen, Y., et al. [17]. This is a nonlinear process that necessitates ongoing evolution and adaptation as the business model and digital technology interact constantly. It may result in business disruptions as well as fresh opportunities. The economic analysis of rehabilitation strategies for water distribution networks in Egypt and Malaysia, which entails a comparative examination of costs, benefits, and prospective effects on the system's efficiency and effectiveness, has been covered by Farouk, A. M., et al. [18]. A variety of factors are assessed, including technology, infrastructure, and management techniques, in order to ascertain the best practical and economical course of action for enhancing water distribution in both nations. The Data Storage and Reliability Analysis on the Internet of Things (IoT) based on Pyramid Code, a technique for arranging and storing data gathered from diverse IoT devices in a hierarchical framework, has been covered by Zhao, X. et al. [19]. It uses redundancy and error-correction techniques to guarantee data accuracy and reliability. It enhances the IoT system's overall effectiveness and performance. Model-free sensor placement, which uses genetic algorithms and clustering techniques to identify the best sites for sensors in a water distribution network, has been covered by Romero-Ben, L., et al. [20]. Since it doesn't rely on a pre-established hydraulic model, it can be used in networks with obsolete or insufficient data. This method enhances water distribution systems' decision-making and monitoring. Roy, S., et al. [21] have talked about In solar power systems, photovoltaic (PV) inverters are essential parts that might fail and cause large financial losses. Unsupervised machine learning techniques can be applied to historical data to find patterns and trends that can be used to estimate and anticipate inverter failures. It can be used in conjunction with reliability assessment techniques to raise the general dependability of PV inverters and increase the accuracy of failure forecasts. Singh, S., et,al.[22] have discussed The framework combines Federated Learning and blockchain technology to address privacy concerns in sharing IoT healthcare data. It allows data to be analyzed and used for improving healthcare without compromising individuals' sensitive information by securely storing and sharing data in a decentralized manner. Nova, K. et,al.[23] have discussed AI-enabled water management systems that combine artificial intelligence technology with traditional water management practices to improve efficiency and conservation. System components may include sensors, predictive algorithms, and data analytics tools to monitor water usage, detect leaks, and optimize distribution. Interdependencies between these components contribute to overall system effectiveness in conserving water resources. Wang, J., et,al.[24] have discussed that Exosome-based drug delivery systems face several challenges, such as a limited understanding of exosome biology, difficulties in large-scale production, and a lack of standardized isolation methods. Additionally, these systems must navigate the complexities of targeting specific cells and tissues in the body and ensuring efficient and safe delivery of drugs. Catelani, M., et,al.[25] have discussed The E-SHERPA method is used for evaluating human errors in railway engineering by considering both task-related and cognitive factors. It combines traditional human reliability analysis techniques with probabilistic methods to provide a more comprehensive and accurate assessment of human performance. It helps in identifying potential human error risks and improving the safety and efficiency of railway systems. Luo, Y., et al.[26] have talked about how ramp current—the greatest current that can flow during a sudden increase in load—can be used to compute the worst-case voltage noise for a power distribution network. Voltage dips and spikes caused by this current can be calculated to make sure the network can withstand these variations. The methods for assessing the reliability of drone swarms, or fleets, have been reviewed by Zaitseva, E., et al. [27]. These approaches entail assessing each drone and its control system separately as well as examining the swarm's overall structure. In order to better comprehend each drone's dependability and potential hazards, a novel importance evaluation-based method considers each drone's functional value within the swarm. Industry 4.0 adoption, or the incorporation of cutting-edge digital technologies like automation, artificial intelligence, and the Internet of Things into manufacturing processes, has been covered by Bag, S., et al. [28]. The development of 10R capabilities—speed, flexibility, and adaptability—which are essential for sustainable development, is made possible by this. Future developments will be more sustainable as a result of these breakthroughs, which enable more productive output, less waste, and better resource management. According to Liu, R., et al. [29], nanoparticles are submicroscopic particles with special physicochemical characteristics that make them perfect for use in drug delivery systems. They contain diverse drug-carrying capacities, regulated release mechanisms, and can be designed to target particular cells or tissues. It makes disease detection and therapy more focused and efficient. The Blockchain and a PUF-based lightweight authentication system have been examined by Wang, W., et al.[30] as a security measure for wireless medical sensor networks. Physically unclonable functions (PUFs) and Blockchain technology are used to allow safe and effective communication between medical sensors and devices. By guaranteeing the legitimacy and consistency of information shared across the network, it safeguards patient confidentiality and deters unwanted access.

Table 1: Comprehensive Analysis

Authors	Year	Advantage	Limitation
Zhu, J., et. al [16]	2024	The model allows for determining the optimal configuration that minimizes the number of affected customers during an outage.	The model may not account for complex reliability issues such as load variability and cascading failures.
Chen, Y., et. al [17]	2021	Increased flexibility in adapting to changing market needs and customer preferences through the integration of digital technology in the business model.	The ever-evolving nature of technology may require constant updates and changes to the business model, leading to increased costs and resource allocation.
Farouk, A. M., et. al [18]	2023	The advantage of economic analysis is	Difficulty in obtaining accurate

		that it allows for a cost-effective comparison between rehabilitation approaches, leading to efficient use of resources.	data on rehabilitation costs and benefits due to different accounting practices and varying levels of technology used in the two countries.
Zhao, X. et. al [19]	2024	The advantage is that it allows for efficient and secure storage of large amounts of data, ensuring reliable analysis for decision-making.	One limitation is data overload, as the large amount of data collected by IoT devices can overwhelm storage systems and make data analysis challenging.
Romero-Ben, L., et. al [20]	2022	It can offer reliable sensor placement solutions without requiring one to have any prior understanding of the network's features.	Model-free approach may not be optimized for networks with complex topology or require prior knowledge about network behavior.
Roy, S., et. al [21]	2024	The use of unsupervised machine learning allows for more accurate and efficient estimation of inverter failure mechanisms without the need for labeled data.	May not accurately predict failure mechanisms in all PV inverters due to variations in operating conditions, system design, and component quality.
Singh, S., et. al [22]	2022	Improved data security and confidentiality through decentralized storage and distributed data sharing.	Limited scalability due to resource-intensive nature of blockchain and potential slow convergence of Federated Learning algorithms.
Nova, K. et. al [23]	2023	Real-time data analysis and decision-making capabilities allow for optimized water usage, resulting in increased efficiency and conservation.	Inability to predict or account for unpredictable environmental factors or human behavior, leading to potential inefficiencies or failures in water management.
Wang, J., et. al [24]	2021	The ability to target specific cells and tissues, providing more effective and precise drug delivery for certain diseases and conditions.	Lack of standardized manufacturing and isolation protocols for exosomes in terms of purity and yield.
Catelani, M., et. al [25]	2021	The E-SHERPA method allows for a systematic and comprehensive analysis of human factors, resulting in improved safety and reliability.	Limited applicability to rare and complex events due to reliance on subjective expert judgments.
Luo, Y., et. al [26]	2024	Accurate prediction of potential voltage fluctuations, allowing for better design and optimization of the power distribution network.	A limitation is that it does not take into account transient effects and non-linearities in the power distribution network.
Zaitseva, E., et. al [27]	2023	The advantage of reliability assessment methods is that they can accurately predict potential failure points and improve overall performance.	Reliability assessment methods only focus on individual drones and do not consider the interactions and dependencies within the swarm.
Bag, S., et. Al [28]	2021	Improved efficiency and reduced waste through automation and digitalization can lead to more sustainable and eco-friendly production practices.	One limitation is that it can widen the digital divide and create unequal access to advanced manufacturing technologies, hindering progress towards

			sustainable development.
Liu, R., et. al [29]	2023	By concentrating on particular cells or tissues, nanoparticles can improve medication efficacy while lowering the risk of adverse effects.	One major limitation is that nanoparticles may cause toxicity and adverse effects in the body if not properly designed and targeted.
Wang, W., et. Al [30]	2021	The combined use of Blockchain and PUF provides strong security and tamper-proofing for collected medical data in a decentralized manner.	The reliance on multiple sensors for authentication may introduce complexity and increase the cost of implementation.

- Aging Infrastructure: One of the significant issues in the reliability assessment of distribution networks is the aging infrastructure. Many distribution networks are built with outdated equipment and technologies, leading to frequent breakdowns and power outages.
- Insufficient Maintenance: Due to tight budgets and limited resources, distribution networks may not receive the necessary maintenance and upgrades. It can result in equipment failure and system disruptions, affecting the reliability of the network.
- Weather-Related Events: Extreme weather events such as storms, hurricanes, and heat waves can severely impact the reliability of distribution networks. These events can cause power outages and damage to the infrastructure, leading to extended periods of downtime.

Because it has such a big impact on data analysis, the utilization of numerous data sources has been receiving a lot of attention lately. Utilizing numerous data sources essentially entails merging many datasets from various sources to obtain a more thorough grasp of a certain subject or event. This approach allows researchers and analysts to access a vast amount of information that would be impossible to obtain from a single dataset. Not only does this increase the quantity of data, but it also enhances the depth and complexity of the analysis.

2. Proposed system

A. Construction diagram

- **Input system configuration:**

The input system configuration is an integral part of any computer or device that requires user input, such as a keyboard or mouse. It is responsible for managing the communication between these input devices and the operating system, allowing the user to control and interact with the computer. At its core, the input system configuration is a software component that acts as an interface between the physical input devices and the operating system. It is responsible for translating the signals from the input devices into meaningful commands that the operating system can understand and act upon.

The operational temperature and sun irradiation of the places where PV systems are deployed determine the PV system's output power. The PV system's output power can be stated as

$$f_{ft}\left(q\left(v\right)\right) = \mu_{cells} PT * B \tag{1}$$

$$Vldv = V_{jv} + q\left(v\right) * \left\{\frac{NOCT - 20}{08}\right\} \tag{2}$$

$$P_e^{obj} = \max\left(P_{WDG}^{obj} - P_{DG}^{obj}\right). \tag{3}$$

$$P_{wdg}^{obj} = \sum_{b=1}^{m}\left(y_g EENS_{DG} + ECOST_{CE}\right)\$ / yr \tag{4}$$

The following limitations are placed on the objective function based on

$$\sum_{b=1}^{m} F_{6,b}\left(v\right) + F_{utility} = \sum_{b=1}^{m} RF_b \tag{5}$$

where is the total amount of power generated by the ESS and renewable energy units,

This translation is necessary because input devices, such as keyboards, use a specific set of codes to represent different keys.In contrast, the operating system may use a different set of codes to represent the duplicate keys.

The operation of the input system configuration detects the input devices. When a device is connected to the computer, the configuration system detects its presence and identifies it according to its type. It allows the system to communicate with the device correctly and receive input signals.

- **Analyze bus outage data:**

"Analyze bus outage data" refers to the process of examining and evaluating information related to power outages that affect electric buses, which are a form of public transportation that run on electricity. This type of analysis is essential for understanding the underlying causes of outages and developing effective strategies for preventing and mitigating them in the future. To begin the study, relevant data was collected from multiple sources, including utility companies, transit agencies, and manufacturers. The construction diagram has shown in the following fig.1

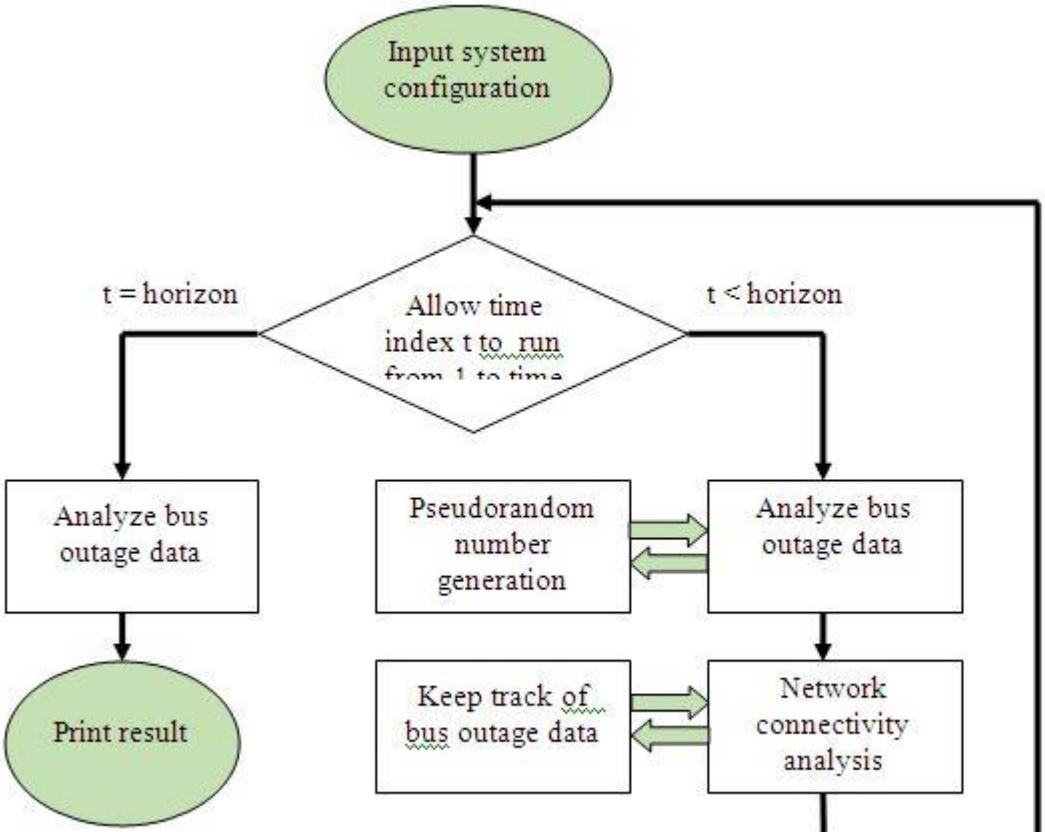


Fig 1: Construction diagram

The quantity and length of outages, meteorological conditions, grid infrastructure, and maintenance logs are a few examples of this data. Accurate and complete data collection is essential to guarantee a full comprehension of the outage events. Following collection, the data is arranged and analyzed using a variety of analytical methods, including statistical analysis, root cause analysis, and fault tree analysis.

P4ðtÞ is the power that moves from the battery to the load during the charging process, P5ðtÞ is the total power produced by WTG, and the battery itself. III. Limitations of the battery storage mechanism

$$SOC^{\min} \leq \left(SOC(o) + \mu_D \sum_{v=1}^{v} F_3(v) - \mu_c \sum_{v=1}^{v} F_4(v) \leq SoC^{\max} \right) \tag{6}$$

$$SOC^{\min} = (1 - DOD) SOC^{\max} \tag{7}$$

These methods assist in finding patterns and trends in the outage data, figuring out the most frequent reasons for outages, and locating any possible system weaknesses.

- **Pseudorandom number generation:**

  Pseudorandom number generation is a process used to create a sequence of numbers that appear random. Computer algorithms generate these numbers and are not truly random, as a set of initial values called seeds determine them. However, the generated numbers are unpredictable and indistinguishable from truly random numbers, making them useful in many applications. The process of pseudorandom number generation involves selecting a seed or set of seeds. It is usually done using system time and other variables, like the computer's unique identification number.

  The system's transition matrix for the whole network is shown in

$$S = \left[1 - \lambda_{zve} - \lambda_{rec} - \lambda_{inv}\right] \tag{8}$$

  The figure depicting the Markov state transition is displayed, with k and l standing for the system failure and repair rates, respectively. The following is an expression for the likelihood of the system in both the up and down states:

$$F_{Down} = \frac{\lambda}{\lambda + \eta} \tag{9}$$

$$F_{of} = \frac{\eta}{\lambda + \eta} \tag{10}$$

$$\lambda_q = \sum_{b \in q} \left(\lambda_b^{'} + \lambda_b^{''} \right) \tag{11}$$

$$O_q = \sum_{b \in q} \left(\lambda_b^{'} l_b^{'} + \lambda_b^{''} l_b^{''} \right) \tag{12}$$

  The exponential distribution has been proposed by numerous researchers for f (t) in sophisticated formulations involving multiple parameters in several cases.

  Next, the pseudorandom number generator (PRNG) technique uses these seeds as inputs. To create a new number, the PRNG algorithm takes the original seed values and applies a number of mathematical operations to them. In the series, this number becomes the subsequent output. After that, the procedure is repeated, using each fresh production as the starting point for the subsequent iteration. A lengthy series of numbers that seem random but are actually deterministic is the end result.

- **Network connectivity analysis:**

  Network connectivity analysis is a process used to assess the health and efficiency of a network by analyzing its connectivity patterns. This analysis involves examining the network infrastructure and traffic flows to identify potential issues or bottlenecks affecting the network performance. Network connectivity analysis gathers data on the network's infrastructure. It can include information such as the types of devices and their configurations, the network topology, and the available bandwidth.

  Table 1 shows a representative sample of the loadpoint reliability indices, the indices are equal to the calculation results of literature.

$$ASAI = \frac{8760 \sum_{b} M_b - \sum_{b} M_b O_b}{8760 \sum_{b} M_b} \tag{13}$$

  Assuming that every element is in a two-state configuration, the likelihood of the system state is equal to

$$\Pr_{\Phi_b} = \prod_{y=1}^{M_d + M_f} J_y^{(1-\ell_b, y)} O_y^{b,y}, \tag{14}$$

  Next, a network map—a graphic depiction of the network—is made using this data. Visually identifying connections between devices and analyzing information flow between them are done with the help of the network map. It allows for the identification of any unnecessary or inefficient connections and the optimization of the network's layout.

- **Keep track of bus outage data:**

  The "Keep track of bus outage data" operation is a crucial aspect of monitoring and managing the performance and reliability of bus systems. It involves systematically recording and tracking information about any outages

or disruptions that occur on the bus network. The process starts with collecting outage data, typically done through automated systems or manual reporting by bus operators and maintenance personnel.
A part of the likelihood of the state transfers to the state, which is how (7) and (9) differ from each other in terms of state updating. Thus, the likelihood of is updated as

$$\overset{New}{\underset{\Phi_b}{\Pr}} = \underset{\Phi_b}{\Pr} + \zeta \times \underset{\Phi_b}{\Pr} \tag{15}$$

where is the probability percentage that transfers to and is the state updating coefficient.
With the exception of the power element not failing, the elements of are comparable to those of in this case. The connection between the components of and is displayed as

$$\ell_{a,y} = \begin{cases} \ell_{b,y} & y \neq \delta \\ 0 & y = \delta \end{cases}. \tag{16}$$

Where is the cyber element that is unavailable? Thus, the likelihood of a state is

$$\overset{New}{\underset{\Phi_b}{\Pr}} = O_\gamma \times \frac{\lambda_\delta}{\lambda_\delta + \eta_\delta} \tag{17}$$

$$L(v) = \int_v^\infty p(v) cv \tag{18}$$

This data includes details such as the route, time, duration of the outage, and the cause of the disruption. The data may also include the number of affected buses and passengers and any actions taken to resolve the outage. Once the data is collected, it is entered into a central database or system that serves as a repository for all outage-related information. The data may be easily accessed and organized, which facilitates analysis and the identification of patterns or trends. Measuring the overall performance and dependability of the bus system is one of the key goals of recording bus outage data.

B. Functional working model

- **Data Warehouse :**

A data warehouse is a centralized location where structured, optimally formatted data from multiple sources is kept. A data warehouse's primary objective is to give an organization's data a single source of truth, facilitating decision-makers' access to and analysis of the data they need to make wise business decisions. The data extraction procedure is one of a data warehouse's most important functions. Data extraction from several sources, including operational databases, spreadsheets, and other systems, is required for this. After that, this data is cleaned and converted to guarantee correctness and consistency.

$$p(v) = \lambda . g^{-\lambda v} \tag{19}$$

$$L = p_0 \left[l_0 + \sum_{r=1}^{MR} l_r \frac{o_r}{j_r} \right] \tag{20}$$

both in the case where component l is in a condition of failure (r0) and in the absence of any failure. Al and ul for each component l can be calculated as follows with knowledge of MTTF and MTTR:
The ratio of the volume delivered to the volume required at a node in a particular time period T indicates the extent to which the demand is satisfied. The ratio for node j can be expressed as:

$$ID_j = \frac{S_a^{avl}}{S_a^{req}} = \frac{\sum_v^V q_a^{avl}}{\sum_v^V q_a^{req}} \tag{21}$$

This extraction process can be done through various methods, including batch processing, real-time streaming, and direct connections. The next operation in the Data Warehouse is data transformation. This is where the data is converted into a standardized format, making it easier to integrate and analyze. Data transformation involves tasks such as normalization, aggregation, and cleansing. Data normalization ensures that data is stored consistently, while data aggregation combines data from multiple sources to create a more comprehensive view. Finding and correcting any mistakes or inconsistencies in the data is the process of data cleansing. The data is imported into the Data Warehouse after it has been converted. The data must be loaded into a database or file system as part of this data loading storage procedure.

- **Summary Data :**

Summary data, also known as aggregate data, refers to data derived from multiple data points to provide an overview of a larger dataset. It is primarily used for analytical purposes and is the basis for creating charts, graphs, and reports. The operations producing summary data can be categorized into three main steps: data selection, transformation, and aggregation. The first step in the operations of summary data is data selection. This involves identifying the relevant data points that must be included in the summary.

.. Gargano and colleagues previously employed a comparable methodology to assess the likelihood of a specific failure scenario.

$$p_1 = p_0 \cdot \frac{o_1}{j_1} \tag{22}$$

when the failure condition is limited to the pipe L.

It fluctuates between 0 and 1 for all possible nodal pressure values.

$$BF_a = \min(1, \min)\left(\max\left[0, f_{a,v}^{avl}\right] / \ f_a^{req}\right) \tag{23}$$

.. Thus, the pressure reliability indicator at node j can be expressed as follows using Eq. 4:

$$LF_a = \left(p_0 f_a\right)_0 + \sum_{r=1}^{MR} p_1 \left(BF_a\right)_r \tag{24}$$

Numerical models of WDNs schematize the time decay of chlorine concentration using three distinct mechanisms:

Depending on the purpose of the summary, different types of data could be selected, such as numerical, categorical, or time-series data. Data selection is a crucial step as it forms the foundation for the accuracy and relevance of the summary data. Once the data points have been selected, the next step is data transformation. This step involves converting the raw data into a format suitable for summarization. For instance, this could include converting a series of numerical data into categories or calculating averages or percentages from a larger dataset. Data transformation is essential to ensure consistency and standardization of the data and make it easier for further analysis. The final step in producing summary data is data aggregation. This involves combining the transformed data points to create a summary dataset.

- **Metadata :**

Metadata refers to the data that describes other data. In simple terms, it is the information about the characteristics and properties of data. This includes details about how the data was created, what it represents, and how it is formatted and structured. Metadata plays a crucial role in data management and organization, providing context and clarity around the analyzed data. Metadata usually comes in three flavors: administrative, structural, and descriptive. Title, author, keywords, subject, and other details about the content and context of the data are examples of descriptive metadata. The relationships and arrangement of data, especially the connections between various data pieces, are defined by structural metadata.

The three phenomena along pipe I at coordinate x and time t are represented as follows by the quality model incorporated in Epanet that was used in the current calculations:

$$\frac{\partial D_b}{\partial_v} = -o_b \cdot \frac{\partial D_b}{\partial h} + \Theta\left(D_b\right) \tag{25}$$

Where are the decay rate, concentration, and flow velocity?

The following is the definition of the performance indicator for the chlorine concentration in the range of 0 to 1:

$$BD_a = \min\left(1, \min\left(D_a^{AVL} \ / \ d_A^{req}\right)_v\right) \tag{26}$$

For node j, this means that the nodal reliability indicator for water quality characteristics can be expressed as follows:

$$LD_a = \left(p_0 \left(BD_a\right)_0 + \sum_{r=1}^{MR} p_r \left(BD_a\right) r\right) \tag{27}$$

Administrative metadata encompasses details about the technical aspects of data, such as file format, size, and access rights. One of the critical operations of metadata is data discovery. With the vast amount of data being generated and stored, it is crucial to quickly locate and access the relevant data. Descriptive metadata plays a vital role in this process by providing information that allows users to search for data using keywords or specific criteria. Another important function of metadata is data management. Metadata allows for accurate and consistent organization and categorization of data, making retrieving and tracking data easier, especially in large datasets.

- **Raw Data :**

Raw data refers to unprocessed, unedited data collected or generated from various sources. This data type is typically in its purest form and has not been manipulated or transformed. It is the building block of any data analysis process and is crucial in providing valuable insights and information. One of the primary operations of raw data is collection. This involves gathering data from different sources such as surveys, sensors, databases, or social media platforms. The data collected can range from text, numerical values, images, audio, or video.

Because of its strong convergence properties, the Newton-Raphson method was employed to create the current formulation.

$$\sum_{b:X_b<X_a} S_{ba} - \sum_{b:X_b<X_a} S_{ba} = S_a^{req} \tag{28}$$

$$S_{ba} = Y_{ba}^{0.54} \left| X_b - X_a \right|^{-0.46} \left(X_b - X_a \right) \tag{29}$$

After comparing several formulas to describe the pressure dependence of nodal consumption, Gupta and Bhave found that the parabolic relationship [5] provided acceptable accuracy.

$$X_a = X_a^{\min} + L_a \left(S_a^{avl} \right)^{m_a} \tag{30}$$

where j is the minimum needed head at node j, or the value below which the outflow is taken to be zero or the performance is deemed poor. and is the available head at node j.

To guarantee the correctness and applicability of the data, the gathering procedure needs to be properly designed and carried out. After it is gathered, raw data is stored. The functional block diagram is displayed in fig. 2.

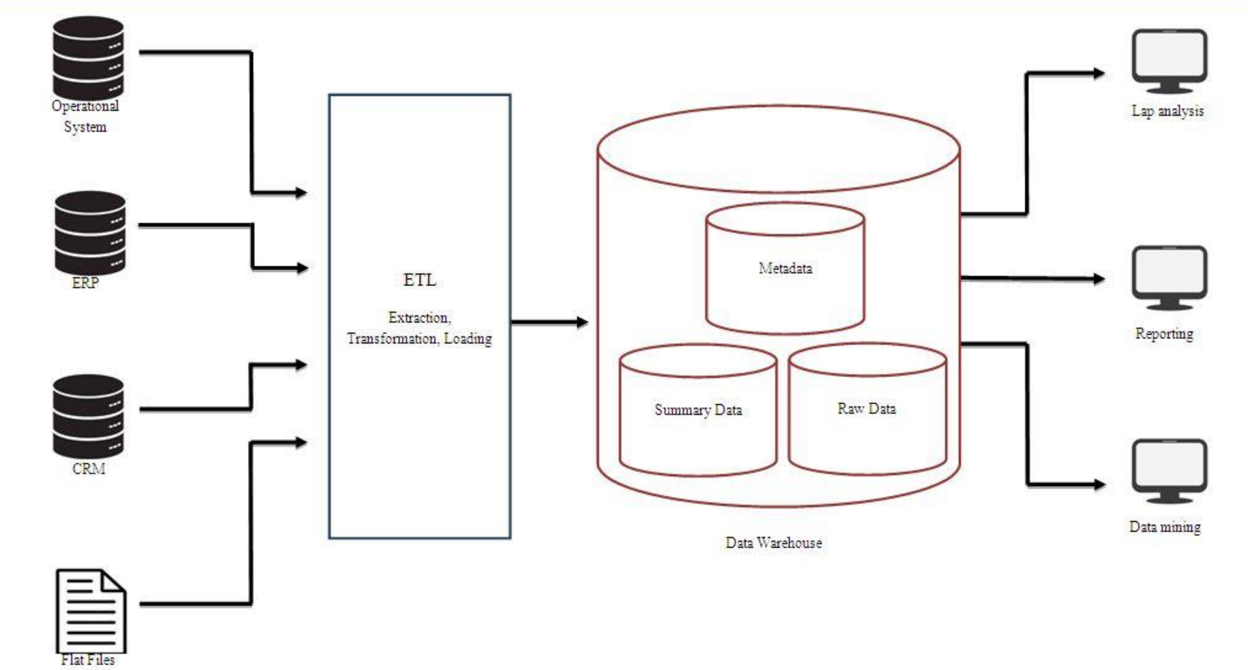


Fig 2: Functional block diagram

This entails keeping the information available and safe for later use. There are many other ways to store data, including flat files, databases, and cloud-based storage solutions. Sufficient raw data storage is essential for convenient retrieval and analysis. Pre-processing or cleaning is the next step for raw data. Finding and eliminating redundant, inconsistent, or irrelevant data is the task at hand. Missing numbers, improper formatting, and outliers in raw data might compromise the quality and dependability of the findings of data analysis.

- **Data mining :**

Finding patterns, connections, and insights in massive data sets is known as data mining. To find important information concealed in data, it entails applying methods from a variety of disciplines, including database systems, machine learning, and statistics. The three primary stages of data mining operations are result interpretation, data analysis, and data preprocessing. Data preprocessing, or cleaning and getting the data ready for analysis, is the first stage in the data mining process. This include eliminating redundant or unnecessary data, adding missing numbers, and formatting the data appropriately.

Gupta and offer a thorough analysis of the several flow-head connections that researchers have put forth.Usually, the partnership is communicated

$$X_a = X_a^{\min} + Y_a S_a^{m_a} \tag{31}$$

where nj is an exponent and Hj is the head at node j when the demand there is a flow resistance coefficient.

At each node, a performance index can be established for the purpose of assessing network dependability as

$$ADF_a = \frac{S_a^{avl}}{C_a} \tag{32}$$

$$ADI_{net} = \frac{\sum_{al \ln odes} S_a^{avl}}{\sum_{al \ln odes} C_a} \tag{33}$$

This is a critical stage since it guarantees that the data is comprehensive and accurate, which is necessary for generating trustworthy findings. The core of data mining is data analysis, which comes next. In order to find patterns and relationships in the preprocessed data, a variety of algorithms and techniques are applied. Classification, grouping, regression, and association rule mining are some of these methods. Every approach has a distinct function, and the choice of methodology relies on the kind of data being examined and the intended result. Interpreting the results is the last step after data analysis. In order to obtain understanding and make wise judgments, the patterns and relationships found in the data are interpreted during this phase.

- **Operational System :**

An operational system, or an operating system, is a crucial component of a computer system. It is a complex software that manages a computer's hardware and software resources and acts as an intermediary between the user and the computer hardware. It is responsible for the overall functioning of the computer, from the moment it is powered on to the point when it is turned off. The primary purpose of an operational system is to provide an efficient and user-friendly interface for users to interact with the computer.

The frequency of occurrence of major adverse weather is given by Equation.

$$S_a^{avl} = Q_a \left(X_a - X_a^{\min} \right)^{\frac{1}{m_a}} \tag{34}$$

where (Hi - Tin) is the residual head, Si is a constant dependent on the outlet characteristics, and nj is an exponent.

$$X_a^{des} = X_a^{\min} + Y_a \left(S_a^{req} \right)^{m_a} \tag{35}$$

$$\left\| \Delta X \right\| = \left[\sum_{A=1}^{MA} \left(\Delta X_a \right)^2 \right]^{1/2} \tag{36}$$

To achieve this, the operating system is divided into several layers, each responsible for a specific task and working together to provide a seamless computing experience. The lowest layer of the operating system is the kernel, which is responsible for managing the computer's hardware resources. It controls the communication between the hardware components and the other operating system layers. The kernel also handles memory management, allocating memory to different processes and ensuring each process has the resources to run effectively. On top of the kernel is the file management system, which is responsible for managing files on the computer. It controls the creation, modification, and deletion of files and their organization and storage on the hard drive.

C. Operating principles

- **Digital Source:**

Digital sources refer to any device or technology that uses digital information or data as its source material. These sources are essential in the modern digital world, where most devices and technologies rely on digital data for their functions. Digital sources encompass a broad range of operations, from data storage and transfer to data processing and display. The operations of digital sources can be understood in three main steps: data collection, processing, and output. The first step in the operation of digital sources is data collection.
Mathematically, reliability R(t) of a component can be expressed as follows:

$$L(v)=\int_{v}^{\infty} p(v)cv \tag{37}$$

Another expression for probability of an operational state of a component has been given as follows.

$$j_r=\frac{\alpha_r}{\alpha_r+\beta_r} \tag{38}$$

where al = expected number of repairs of pipe 1 per unit of time, and 13 / = expected number of failures of pipe 1 over the same period. a t is obtained by evaluation of historic data and p, can be demonstrated as:
Then, the minimum shortfall for the system was calculated by the sum of the shortfall for each state, weighted according to the respective state probabilities as follows:

$$L=1-\sum_{r=0}^{MF} f(r)\left(1-\frac{S_q^{avl}(r)}{S_q^{req}}\right) \tag{39}$$

This involves gathering digital information from various sources, such as sensors, cameras, microphones, and user inputs. These sources capture analog signals converted into digital signals through digitization. Digitization involves sampling the analog signal regularly and assigning a binary code to each sample. This results in a digital representation of the original analog signal, which can be easily stored and processed. The next step in the operation of digital sources is data processing. This involves manipulating and analyzing the collected digital data to extract meaningful information. Data processing can involve various operations, such as sorting, filtering, and transforming the data. For instance, a digital camera processes the digital image data captured by its sensor to create a high-quality photograph.

- **Digital Sink :**

Digital Sink is a software component in a digital transmission system that receives and processes digital data transmitted from a source. It plays a crucial role in the data transmission process by acting as the final destination for the data. This data could be in the form of audio, video, or any other digital format. The operations of the Digital Sink can be broadly categorized into three stages: data reception, processing, and output. The first stage, data reception, involves the Digital Sink receiving the digital data from the source. The data can be transmitted through various means, such as a cable, satellite, or the internet.
. A demand-driven simulation was carried out, then for each node the hydraulic reliability was defined as the probability that the actual nodal pressure is equal to or greater than the minimum required pressure,

$$L_a=f\left(X_a>X_a^{des}\right)=\int_{X}^{\infty} p\left(X_a\right)cX_a \tag{40}$$

where Ri is the nodal reliability at node j, 113 and Hid" are nodal available and minimum required heads at node j, respectively, and f(H3) is the probability density function.
The proportion of time that the demand can be met at or above the target pressure was used to define availability. The model also acknowledged the dependence of demand on pressure. The total nodal availability was found to be

$$J_a=\sum_{v=1}^{MV}\frac{j_a(v)\Delta v}{VV} \tag{41}$$

where node j and time t represent the nodal availability, and a(t) The variables at, TT, and NT represent the time interval, total time, and number of time intervals, respectively.
Next, the arithmetic mean of the nodal availabilities was used to get the system availability, A, as follows:

$$J\sum_{a=1}^{MA}\frac{J_a}{MA} \tag{42}$$

The Digital Sink must be able to receive data in the same format as the source to ensure that the data can be processed accurately. This is achieved by using standard protocols and codecs compatible with the source. Once the data is received, the Digital Sink moves on to the next stage, data processing. This involves the Digital Sink converting the digital data into a format suitable for further processing. The data may be compressed to reduce the size for efficient transmission, and the Digital Sink must decompress it before processing. It also checks for errors in the received data and corrects them using error correction techniques.

- **Channel Encoder :**

To guarantee the dependable transfer of data over a noisy channel, a channel encoder is an essential part of communication systems like wireless and satellite communication. It is in charge of transforming the digital data stream into a format that can be sent over the designated communication channel. A channel encoder's main job is to add redundancy to the data that is conveyed, which increases its resistance to errors brought on by interference or noise in the communication channel. In order to accomplish this, extra bits are added to the original data stream in accordance with preset rules and algorithms. The operating flow diagram is displayed in fig. 3 below.

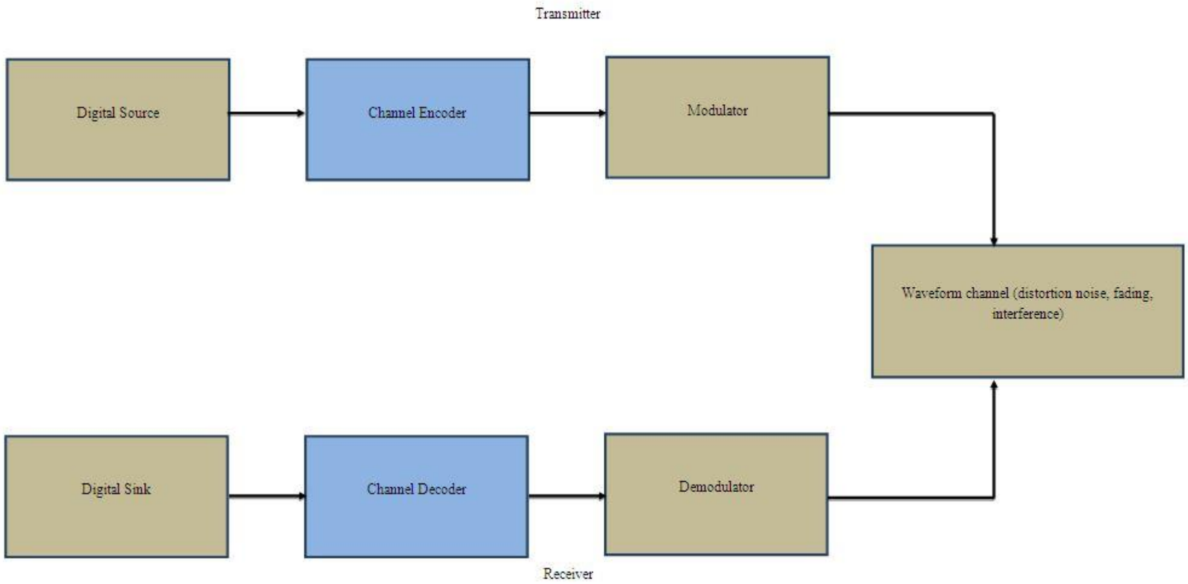


Fig 3: Operational flow diagram

The extra bits, sometimes referred to as parity or check bits, are employed in data transfer to identify and fix potential problems. Error-correcting codes are one of the most widely utilized methods for adding redundancy. Considering the probability of one link failure, the nodal availability is then stated as

In this method a relationship between source head and source outflow (inflow to the system) was applied to determine the flow supplied when service was subnormal. The formulation was as follows:

$$S_q^{avl} = S_q^{req}\left(\frac{X_q}{X_q^{des}}\right)^{\frac{1}{m}} X_q \prec X_q^{des} \tag{43}$$

in which Q and (Ire(' were the available and required source flows, respectively. Hs and Rd ' were the available and desired heads at source, respectively, and n = 2.

The reliability was defined as a ratio between the expected total outflows under adequate pressure and the total demand. Then the reliability at each state was obtained as

$$L = \frac{S_q^{avl}}{S_q^{req}}\alpha\left(\frac{X_q}{X_q^{des}}\right) \tag{44}$$

Tanyimboh (1993) asserted that the actual flow supplied when service is subnormal, should be determined using the head driven simulation.
Consequently, any true network dependability metric should take into account the relationship between actual nodal outflows and pressure (see Chapters 5 and 6). In Chapter 5, the fundamental nodal head-outflow relationship was explained as follows:

$$X_a = X_a^{\min} + Y_a \left(S_a^{avl} \right)^{m_a} \tag{45}$$

These codes assign specific bit patterns to the data bits and check bits, making it possible to detect and correct errors in the received data. A popular type of error-correcting code is the Hamming code, which adds redundant bits to the data stream in a specific pattern, allowing for the correction of a single-bit error. In addition to error correction, Channel Encoders can also employ other techniques to facilitate reliable data transmission.

- **Channel Decoder :**

Channel Decoding is an essential process in wireless communication systems that allows for accurate data transmission. It is responsible for correcting errors that may occur during the transmission of information by the channel, which can be affected by noise, interference, and fading. The first step in channel decoding is to receive the transmitted signal, which is affected by the channel's properties. This signal is then passed on to the channel decoder, designed to analyze its structure and identify any errors that may have occurred. The decoder uses mathematical algorithms to compare the received and expected signals based on the initially transmitted data.
The likelihood that each of the remaining (NP-M) links is available and only the M stated links are unavailable, or p(M), is provided by

$$F\left(N\right) = f\left(0\right) \prod_{r=1}^{N} \frac{oj_r}{j_1} \quad N = 1, \ldots, MF \tag{46}$$

$$l_a\left(N\right) = \frac{S_a^{avl}\left(N\right)}{S_a^{req}} \quad N = 0, \ldots, MF; \forall a \tag{47}$$

One of the most common techniques used in channel decoding is Forward Error Correction (FEC). This method adds extra bits to the transmitted data, allowing the decoder to check for errors and correct them without retransmitting. This not only saves time but also improves the reliability of the data transmission. Another commonly used technique is Maximum Likelihood (ML) decoding, which uses statistical analysis to determine the most likely transmitted data sequence. ML decoding requires knowledge of the channel's characteristics, such as the signal-to-noise ratio, to accurately determine the transmitted data.

- **Modulator :**

A modulator, also known as a modulation unit, is a device or module used in electronic systems to manipulate signal characteristics. It alters the properties of a carrier signal by modulating it with a lower-frequency input signal. This process is essential in many electronic systems, as it allows transmitting information through a carrier signal. The modulator's primary function is to alter the carrier signal's amplitude, frequency, or phase by the input signal. This is achieved through modulation, where the input signal is superimposed onto the carrier signal, causing changes in its properties. The resulting modulated signal then carries the input signal information and can be transmitted through a medium.
Here, an alternative method based on matrix calculations has been applied, negating the need for specialized understanding of graph theory.

$$\left|D\right| \times \left|D\right|^{V} = T = R + 2B \tag{48}$$

where the identity matrix I multiplied by two and the line or edge graph matrix add up to the symmetric matrix V.
This also holds true for L's non-zero elements.

$$T^2 = \left(R + 2B\right)^2 = R^2 + 4R + 4B \tag{49}$$

Three types of modulators are most frequently used: phase, frequency, and amplitude modulators. Each has a different way of working. The carrier signal's amplitude is changed in an amplitude modulator in accordance to the input signal.A frequency modulator, on the other hand, modifies the carrier signal's frequency in response to the input signal. In contrast, a phase modulator modifies the carrier signal's phase in order to encode the input signal. Usually, the modulator is made out of a circuit that mixes the carrier and input signals and uses the proper modulation method.

- **Demodulator :**

A demodulator is an electronic device that recovers the original information signal from a modulated carrier signal. The carrier signal is used to carry the information through a channel, which could be a wire, fiber optic cable, or wireless transmission. Demodulators are commonly used to retrieve the transmitted audio or video signal in communication systems, such as radio, television, or telephone. The operation of a demodulator starts with the reception of the modulated carrier signal. This signal combines the original information signal and the carrier signal. The modulated carrier signal is then passed through a bandpass filter, which isolates the carrier frequency from the other frequencies present in the signal.

Betweenness centrality of a node (ni∈ N) is used to express the relative importance of each node in the graph. It is provided by

$$D_I\left(b\right)=\sum_{n_b\neq m_y\neq m_1}\frac{m_y\rightarrow m_r,m_b}{m_y\rightarrow m_r} \tag{50}$$

Consequently, for a given configuration, the distribution system's overall topological resilience is given by

$$\Re_\tau=\sum_{a=1}^{\eta}T_a\rho\left(b,a\right)' \tag{51}$$

Although a distribution network with high topological resilience can be designed, it might not be able to withstand physical restrictions.

This step is essential as it removes any possible interference and noise that may have been picked up during the transmission. After the carrier frequency is extracted and sent to a demodulation circuit, this circuit separates the carrier signal from the information signal. Different types of transmission are suitable for different types of demodulation techniques, such as phase modulation (PM), frequency modulation (FM), and amplitude modulation (AM). The demodulation circuit performs the inverse process of the corresponding modulation technique used at the transmitter, thus recovering the original information signal.

4. Result and Discussion

The performance of proposed method Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) have compared with Probabilistic Reliability Indices Method (PRIM), Multi-Source Data Reliability Assessment (MDRA) and Integrated Data Sources (IDS).

4.1. Data Accuracy:

The reliability assessment of distribution networks relies heavily on accurate and complete data from multiple sources. It includes data on equipment, operational performance, outage events, and customer load profiles. Technical performance parameters could include metrics for data quality, such as data accuracy, timeliness, completeness, and consistency across different sources. Table.2 shows the comparison of Accuracy between existing and proposed models.

Table.2: Comparison of Accuracy (in %)

No. of Images	PRIM	MDRA	IDS	TOPSIS
100	83.26	74.71	82.48	91.84
200	81.76	74.12	80.61	90.83
300	80.65	73.14	79.78	90.67
400	80.27	71.93	78.87	89.71
500	79.26	70.79	77.95	90.14

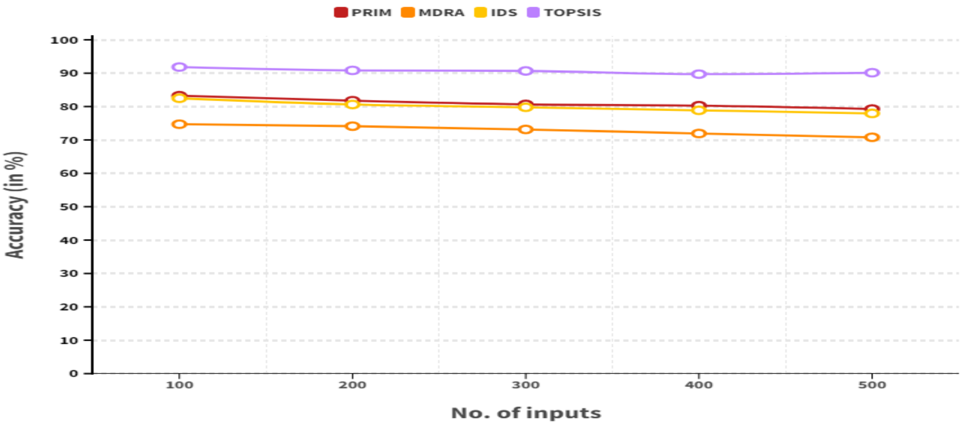


Fig.4: Comparison of Accuracy

Fig. 4 shows the comparison of Accuracy . In a computation cycle, the existing PRIM obtained 79.26%, MDRA obtained 70.79%, IDS reached 77.95 % Accuracy. The proposed TOPSIS obtained 90.14 % Accuracy.

4.2. Interoperability:

Interoperability refers to the ability of different data sources to communicate and exchange information seamlessly. In the context of reliability assessment, this could include technical measures like data format compatibility, data transfer protocols, and data integration capabilities between different sources. A high level of interoperability ensures that data from multiple sources can be effectively used in the assessment process, leading to more accurate and reliable results. Table.3 shows the comparison of Interoperability between existing and proposed models.

Table.3: Comparison of Interoperability (in %)

No. of Images	PRIM	MDRA	IDS	TOPSIS
100	81.26	76.71	84.48	89.84
200	79.76	76.12	82.61	88.83
300	78.65	75.14	81.78	88.67
400	78.27	73.93	80.87	87.71
500	77.26	72.79	79.95	88.14

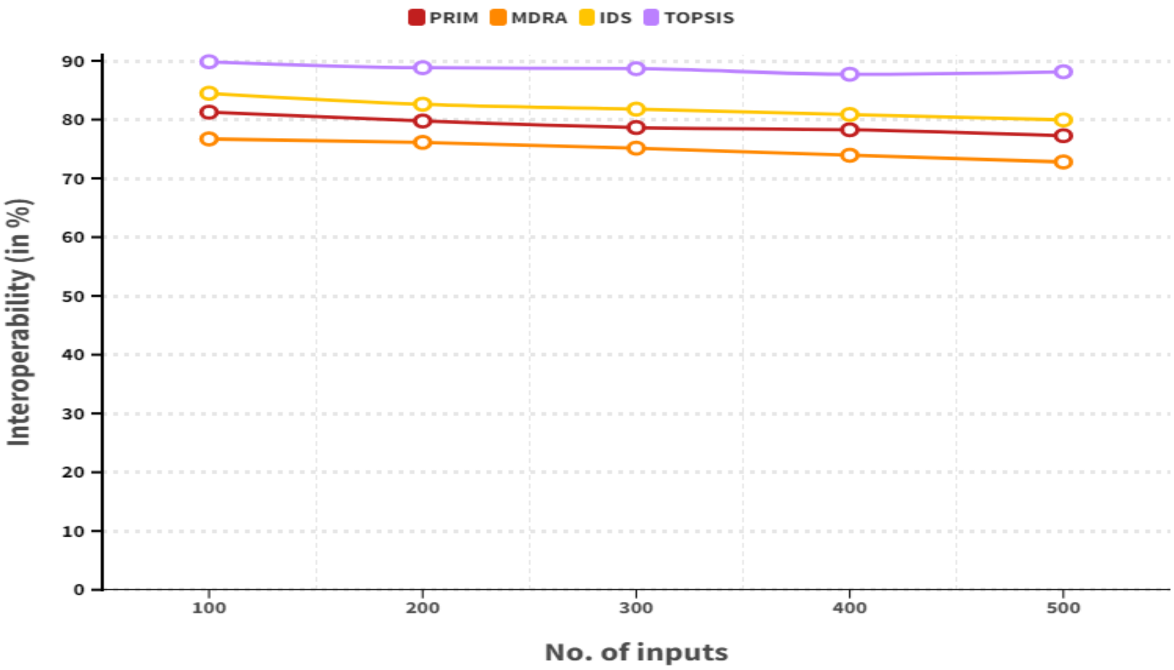


Fig.5: Comparison of Interoperability

Fig. 5 shows the comparison of Interoperability . In a computation cycle, the existing PRIM obtained 77.26%, MDRA obtained 72.79%, IDS reached 79.95% Interoperability. The proposed TOPSIS obtained 88.14% Interoperability.

4.3. Scalability:

As the size and complexity of distribution networks continue to increase, the ability to handle large volumes of data becomes crucial. The technical performance parameter of scalability refers to the ability of data sources to support the increasing demands for data storage, processing, and analysis. It includes parameters like data storage capacity, processing speed, and analytics capabilities, which are essential for conducting comprehensive reliability assessments of large distribution networks. Table.4 shows the comparison of Scalability between existing and proposed models.

Table.4: Comparison of Scalability (in %)

No. of Images	PRIM	MDRA	IDS	TOPSIS
100	84.26	79.71	88.48	91.84
200	82.76	79.12	86.61	90.83
300	81.65	78.14	85.78	90.67
400	81.27	76.93	84.87	89.71
500	80.26	75.79	83.95	90.14

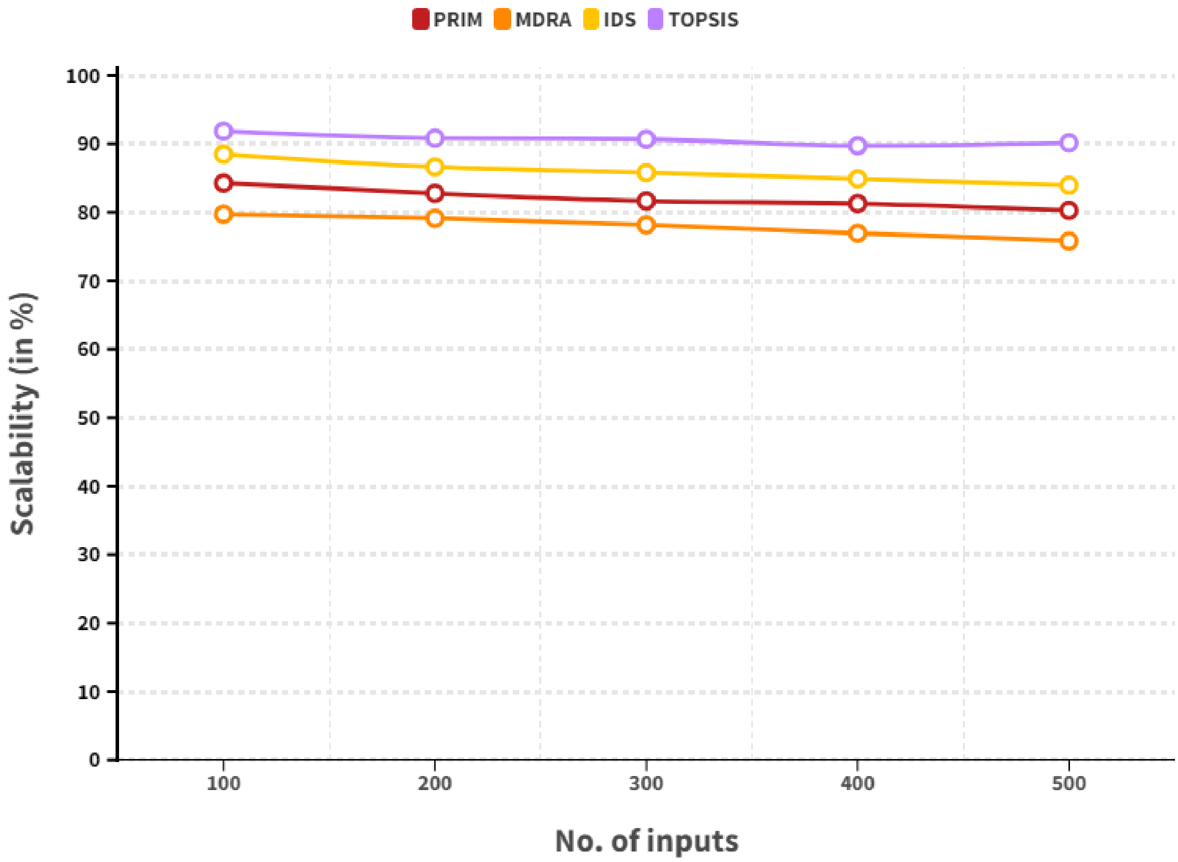


Fig.6: Comparison of Scalability

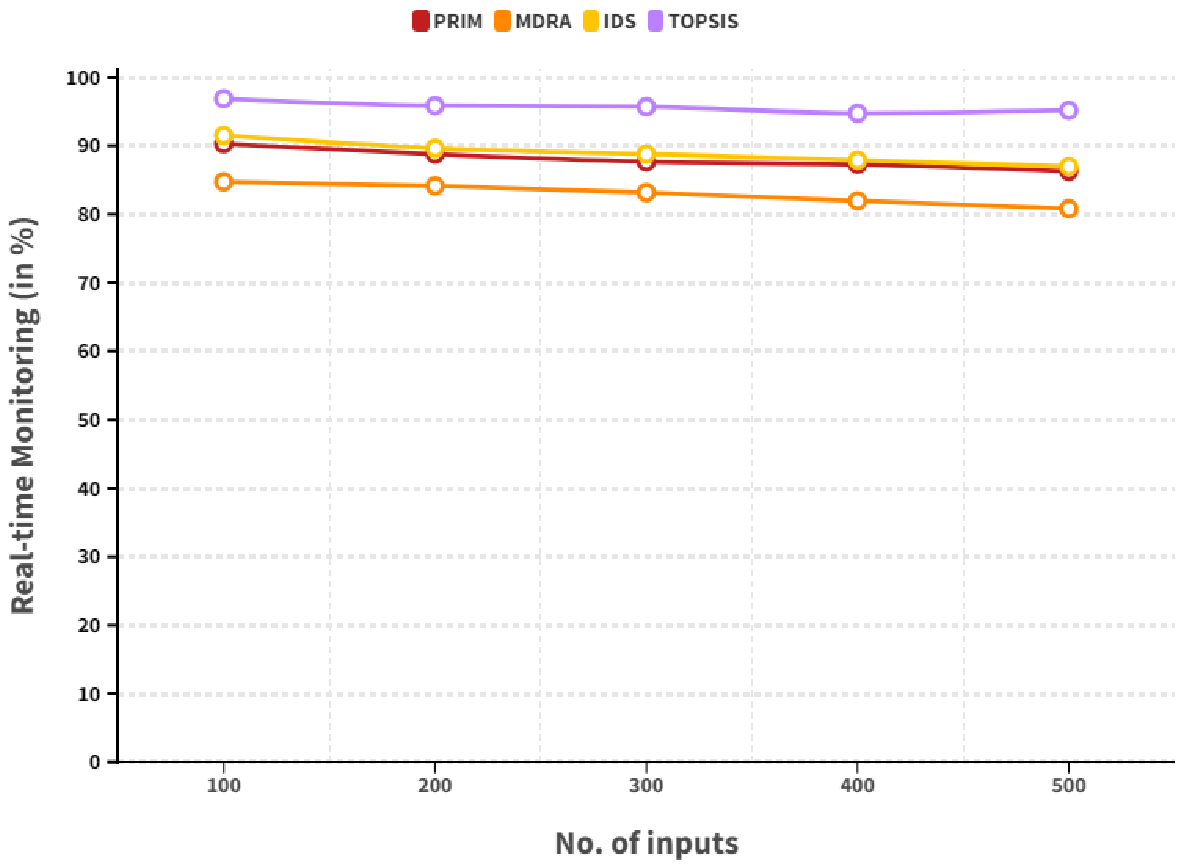
Fig. 6 shows the comparison of Scalability . In a computation cycle, the existing PRIM obtained 80.26%, MDRA obtained 75.79%, IDS reached 83.95% Scalability. The proposed TOPSIS obtained 90.14% Scalability.

4.4. Real-time Monitoring:

Many modern distribution networks rely on real-time monitoring and control systems to improve network reliability. In this case, the technical performance parameter for data sources would include the ability to provide real-time data on network conditions, such as equipment status, outage events, and load levels. The data sources should also be able to generate real-time reports and alerts, enabling quick response and corrective actions to minimize the impact of network disruptions. Table.5 shows the comparison of Real-time Monitoring between existing and proposed models.

Table.5: Comparison of Real-time Monitoring (in %)

No. of Images	PRIM	MDRA	IDS	TOPSIS
100	90.26	84.71	91.48	96.84
200	88.76	84.12	89.61	95.83
300	87.65	83.14	88.78	95.67
400	87.27	81.93	87.87	94.71
500	86.26	80.79	86.95	95.14



ig.7: Comparison of Real-time Monitoring

Fig. 7 shows the comparison of Real-time Monitoring . In a computation cycle, the existing PRIM obtained 86.26%, MDRA obtained 80.79%, IDS reached 86.95 % Real-time Monitoring. The proposed TOPSIS obtained 95.14 % Real-time Monitoring.

5. Conclusion

In conclusion, using multiple data sources in the reliability assessment of distribution networks allows for a more comprehensive analysis and understanding of the network's performance. By combining data from various sources, such as outage records, maintenance logs, and customer feedback, a more accurate assessment of reliability can be obtained. This approach can also identify patterns and trends that may not be apparent when using one data source alone. Ultimately, the use of multiple data sources can lead to more targeted and effective reliability improvement strategies, resulting in a more reliable distribution network.

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