J. Electrical Systems 20-7s (2024): 2026-2046

[1]Ling Liang,
[1]Zhongqiang Zhou*,
[2]Hai Qin,
[1]Ying Lu,
[1]Huijiang Wang

An Improved Analysis of Distributed Resource Access Location and Capacity on Voltage Stability of Distribution Networks in Smart Grid

JES Journal of Electrical Systems

Abstract: - Concerns about how Distributed Energy Resources (DERs) may affect distribution network voltage stability have been brought up by the widespread usage of DERs in the elegant Grid. A Smart Grid connects a range of distributed energy resources (DERs) to the distribution network, including electric cars, wind turbines, and solar panels. This connection can alter the working conditions of the network. These changes can lead to voltage stability problems, which can affect the overall efficiency and reliability of the Smart Grid. Thus, there is a need for an improved analysis of the effects of Distributed Resource Access Location and Capacity (DRALC) on voltage strength in distribution networks. Here, we propose an improved analysis of the impact of DRALC on voltage stability in distribution networks in the Smart Grid. Our analysis considers the location and capacity of DERs and their effect on voltage stability using a combination of analytical and simulation methods. We first develop a mathematical model to represent the distribution network, which includes the DERs as voltage sources. Next, we use the voltage stability index and load flow analysis to evaluate the voltage stability of the network under different DRALC scenarios. Finally, we validate our analysis by performing simulations on a real-world distribution network.

Keywords: Smart Grid, Multi, Distribution Network, Improved Analysis, Mathematical Model, Voltage Stability, Interconnected

1. Introduction

Voltage strength is a serious aspect of the process of distribution networks in the smart grid. In traditional power systems, voltage stability is controlled through centralized voltage regulation, which involves adjusting the tap positions of transformers and reactive power compensation devices [1]. This approach is not practical due to the growing interconnectedness of distributed energy resources (DERs) with the distribution network in an intelligent grid. DERs are usually connected to the low-voltage distribution network and can significantly affect voltage stability. Renewable energy sources (DERs) include wind turbines, solar photovoltaic (PV) systems, and electric cars [2]. The location and capacity of these resources must be considered in order to ensure the stability of the distribution network. One solution to this issue is the Distributed Resource Access Location and Capacity (DRALC) concept [3]. DRALC is a method that uses DER placement and sizing to strategically improve

[1] 1.Guizhou Grid Electric Power Dispatching and Control Center，Guiyang Guizhou，550000，China

[2.]Guizhou Grid Zunyi Power Supply Bureau, Zunyi, Guizhou, 563000, China

Corresponding author：Zhongqiang Zhou

Communication mailbox：gzdwzzq@163.com

Ling Liang：lianglingaa@163.com

Hai Qin：13618586752@139.com

Ying Lu：luying1843@163.com

Huijiang Wang：whj408438504@163.com

voltage stability in the distribution network. The first part of its two-stage optimization process makes sure that the DERs are dispersed throughout the network in a way that improves voltage stability [4].On the other hand, the ideal DER size is decided upon in the second stage. This idea considers a number of variables, including load characteristics, feeder topology, and the placement and capacity of current DERs [5]. It also considers the voltage constraints and the voltage sensitivity of the network. By incorporating these factors, DRALC can effectively identify the optimal location and size of DERs, which can enhance voltage stability in the distribution network [6]. The benefits of using DRALC include improved voltage stability, reduced losses, and better utilization of available network resources. As distribution networks increasingly incorporate distributed energy resources (DERs), DRALC might be a vital component in guaranteeing the smart grid's dependable and secure operation [7]. One important consideration in the planning and management of distribution networks in an intelligent grid is the Distributed Resource Access Location and Capacity (DRALC). It describes the capacity to efficiently manage the capacity of distributed energy resources (DERs) and find and access them at the right points within the network [8]. The power system's capacity to maintain a constant and suitable voltage at all times is largely dependent on its voltage stability[9]. In a distribution network, the scalability and variability of DERs can significantly impact the voltage stability and pose challenges to the distribution system operators. The placement of DERs in a distribution network can cause voltage fluctuations due to the variability in their output. It can lead to overvoltage or under voltage conditions that can compromise the stability of the system [10]. For example, a high concentration of distributed solar PV systems in a specific area can result in excessive voltage rise. In contrast, a high concentration of electric vehicle charging can cause significant voltage drops [11]. The location placement of DERs can also affect voltage stability. DERs located at the end of a long feeder in the distribution network may experience significant voltage variations due to the line impedance. It can result in voltage violations and ultimately affect the strength of the system [12]. The capability of the DERs also plays a vital role in voltage stability. The DERs should have sufficient capacity to balance the load and maintain voltage within an acceptable range. Their variable nature makes it challenging for distribution system operators to predict and manage their capacity [13]. The mismatch between the DER capability and the load demand can result in voltage instability. DRALC is a vital issue in the smart grid as it directly affects the voltage stability of distribution networks [14]. The variability and scalability of DERs, along with their location placement and capacity, can cause voltage fluctuations and instability in the system. Effective management and allocation of DERs are necessary to ensure voltage stability in an intelligent grid distribution network [15]. Voltage regulation, demand response, energy storage, and other advanced control and optimization techniques can be applied in an intelligent grid to handle this problem and preserve the stability of the distribution network. The main contribution of the research has the following:

- The study provides valuable insights into the force of distributed energy resources (DERs) on voltage strength in distribution networks in smart grids. It is an essential contribution as the integration of DERs is significantly increasing in modern power systems.
- The research highlights the importance of accurate resource access location and capacity management for maintaining voltage stability in distribution networks. It can help distribution system operators make informed decisions and better manage the integration of DERs.
- The study presents a comprehensive analysis of the relationship between resource access location and capacity and voltage stability, considering different scenarios and voltage control strategies. It provides a deeper perceptive of the interplay between these variables and can aid in the development of practical solutions for voltage stability in intelligent grid distribution networks.

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

Van Tran, T., et, al. [16] have discussed the reconfiguration of distribution networks involves restructuring the layout of power distribution systems to incorporate distributed generation sources better. An enhanced neural network method can optimize this process by adaptively adjusting the network parameters to effectively integrate distributed generating technologies with renewable energy sources. The hybrid optimization-based technique has been presented by Akbar, M. I., et al. [17] as a novel method for attaining the ideal distribution of Distributed Generators (DGs) in distribution networks. In order to determine the ideal location and capacity for DGs, it combines single and multi-objective optimization approaches, which improves network performance and lowers power losses. The probabilistic evaluation of PV hosting capacity and the amount of solar energy that may be safely incorporated into an unbalanced active distribution system while preserving stable voltage levels are covered by Han, C., et al. [18]. In order to guarantee dependable and effective network functioning, it considers both the probabilistic character of photovoltaic generation and the influence of coordinated voltage regulation. Saidi, A. S. et, al. [19] have discussedGrid-tied photovoltaic (PV) systems, which supply electricity directly to the grid, can cause voltage fluctuations due to their intermittent nature. Dynamic reactive power control can help mitigate these impacts by adjusting the reactive power output of PV systems to maintain voltage stability in the Tunisian distribution network. Lee, J. W., et, al. [20] have discussed this strategy using concepts from game theory to determine the best scheduling plan for multiple agents in a distribution network. It takes into account the voltage management aspect, aiming to maintain optimal voltage levels and minimize losses. The game-theoretic approach considers the decision-making behavior of each agent to reach a globally optimal solution. In Ahmadi, M., et al.'s discussion [21], the best possible coordination of battery storage devices with distributed and centralized renewable power generation inside the electric distribution network. This includes effectively controlling power flow to satisfy demand, reduce losses, and maintain grid stability. Integration of cutting-edge control systems and smart grids can accomplish this. Enhancing the efficiency and cost of power distribution through the use of nature-inspired optimization algorithms is referred to as "improving the techno-economic pattern" for distributed generation-based distribution networks in the discussion by Hassan, A. S., et al. [22]. By optimizing the distribution network's architecture and functioning, these algorithms imitate the behavior of natural systems, improving system performance and lowering operating expenses. Deep reinforcement learning is a sort of artificial intelligence that helps electric cars to make the best charging decisions while taking the stability of the distribution network voltage into account, according to Liu, D., et al. [23]. This method uses data from past experiences and interactions with the environment to make decisions and improve charging efficiency while maintaining a stable voltage. Mahmoud, K., and colleagues [24] have addressed Mathematical formulas known as comprehensive analytical expressions can be used to evaluate the technical advantages of incorporating solar power systems into distribution networks. They can also be used to calculate the highest possible benefit that can be attained through parameter optimization, including configuration, location, and PV capacity. The upgraded approach for solar PV hosting capacity study, as described by Abideen, M. Z. U., et al. [25], makes use of cutting-edge technology and algorithms to calculate the maximum quantity of solar PV that a distribution network can take without having negative effects. In order to produce more precise and trustworthy findings, this method considers a number of variables, including voltage and thermal limitations. Enhancing the efficiency and cost of power distribution through the use of nature-inspired optimization algorithms is referred to as "improving the techno-economic pattern" for distributed generation-based distribution networks in the discussion by Hassan, A. S., et al. [22]. By optimizing the distribution network's architecture and functioning, these algorithms imitate the behavior of natural systems, improving system performance and lowering operating expenses. Deep reinforcement learning is a sort of artificial intelligence that helps electric cars to make the best charging decisions while taking the stability of the distribution network voltage into account, according to Liu, D., et al. [23]. The joint planning of distributed generation (DGs) and energy storage devices in active distribution networks (ADNs) has been described by Li, Y., et al. [30] as a bi-level programming technique that maximizes the DG and energy storage in an ADN's placement and sizing. It allows for efficient utilization and integration of these resources, resulting in improved economic and technical performance of the network.

Table.1 Comprehensive Analysis

Author	**Year**	**Advantage**	**Limitation**
Van Tran, T., et, al. [16]	2021	Improved efficiency and reliability in managing and optimizing power flows due to more accurate and adaptable decision-making capabilities of the neural network	The algorithm relies on accurate data and may not account for uncertainties or errors in input parameters.

		algorithm.	
Akbar, M. I., et, al. [17]	2022	The hybrid approach may determine the best distribution network DG allocations while simultaneously optimizing for single and multi-objective achievement.	One limitation could be the complexity of implementing the hybrid optimization-based approach in practical application.
Han, C., et, al. [18]	2022	One advantage of applying a probabilistic evaluation of PV hosting capacity under coordinated voltage regulation is increased grid dependability and stability.	One limitation may be that the assessment does not consider the impact of extreme weather conditions on PV performance in unbalanced networks.
Saidi, A. S. et, al. [19]	2022	Improved voltage stability by using dynamic reactive power control helps prevent network failures and ensures reliable electricity supply to consumers.	Grid-tied PV systems may increase voltage levels beyond acceptable limits in heavily loaded distribution networks, leading to potential voltage stability issues.
Lee, J. W., et, al. [20]	2022	The optimal scheduling strategy can adapt to changing network conditions and maintain stable voltage levels while minimizing losses and costs.	One limitation of this strategy is its complexity and potential difficulty in implementation and calculation for large-scale distribution networks.
Ahmadi, M., et, al. [21]	2021	economical use of renewable energy sources while maintaining the stability and dependability of the electrical grid.	One limitation is the potential for high costs associated with upgrading or integrating the existing distribution network infrastructure.
Hassan, A. S., et, al. [22]	2022	In order to effectively integrate and utilize renewable energy sources, distributed generation-based distribution networks can become more efficient and cost-effective with the use of optimization algorithms inspired by nature.	The limitation is use of nature-inspired optimization algorithms may not always be applicable or effective in all scenarios or industries.
Liu, D., et, al. [23]	2023	Improves system stability by considering voltage constraints for optimal charging schedule, avoiding overloading and voltage fluctuations.	One limitation is the lack of real-world data and potential inaccuracies in modelling the distribution network voltage stability.
Mahmoud, K., et, al. [24]	2021	Accurate assessment and optimization of the integration of photovoltaics in distribution systems for enhanced efficiency and performance.	Not accounting for non-technical barriers and costs such as land availability and regulatory hurdles.
Abideen, M. Z. U., et, al. [25]	2022	Improved integration of solar PV resources can lead to increased renewable energy generation and reduced carbon emissions in the	Limited accuracy due to simplifications and assumptions made in the analytical approach, may not

		distribution network.	reflect real-world scenarios.
Faraji, E., et, al. [26]	2021	Improved system reliability and security leading to proficient and sure operation of the distribution network.	probabilistic approach may not accurately capture real-time variations in demand and generation, leading to suboptimal control decisions.
Zhan, H., et, al. [27]	2023	One benefit is that it can lessen the chance of power outages and increase the distribution network's dependability.	A constraint pertains to the absence of uniform methodologies for testing and assessing voltage stability in highly permeable active distribution networks.
Haider, W., et, al. [28]	2021	The voltage profile is improved and losses are reduced, leading to improved system efficiency and reliability.	Limited accuracy due to varying network conditions and uncertainties in demand and generation levels.
Rajagopalan, A., et, al. [29]	2022	Increased efficiency and reliability of energy distribution due to optimal management of decentralized energy sources and storage.	Potential difficulty integrating multiple soft computing methods and ensuring accurate data inputs for optimal system performance.
Li, Y., et, al. [30]	2022	Maximizes efficiency and cost-effectiveness by coordinating generation and storage resources to meet demand and reduce network losses.	For large-scale systems with a significant number of distributed generation resources and energy storage devices, the bi-level programming method might not be appropriate.

- Inaccurate Voltage Measurements: One of the main challenges in distributed resource access location and capacity is the potential for inaccurate voltage measurements in distribution networks. The fact that distributed resources, such as solar panels or wind turbines, can cause variations in the voltage at different nodes in the network. It can lead to voltage imbalances and potential voltage violations, which can negatively impact the stability of the system.
- Lack of Real-Time Control: Another issue is the need for real-time control over distributed resources in distribution networks. In traditional distribution networks, voltage control is primarily carried out by the utility through centralized systems. However, with the integration of distributed resources, the control and coordination of these resources become more complex and challenging to manage. It can result in voltage fluctuations and impacts on voltage stability.
- Lack of Coordination among Distributed Resources: The successful integration of distributed resources into distribution networks requires coordination among these resources to ensure reliable voltage control. However, this coordination is often lacking, as distributed resources are typically owned and operated by different entities. It can lead to conflicts and inconsistencies in voltage control strategies, which can have a significant impact on the stability of the network. Additionally, communication and information exchange among distributed resources may also be limited, further hindering effective coordination for voltage stability.

The thorough examination of the effects of capacity and Distributed Resource Access Location (DRAL) on the voltage stability of distribution networks in the smart grid is the technical innovation of this work. Numerous factors are included in this study, including the operational conditions of the power system and the kind, location, and capacity of distributed energy resources (DERs). By taking into account how DERs affect the voltage profile of the network, this study creates a novel technique for assessing the voltage stability of distribution networks. This study broadens the analysis to include the effects of DERs, since the majority of previous studies on voltage stability solely address the effects of conventional generators and loads. The Distributed Resource Sensitivity Coefficient (DRSC), which measures each DER's contribution to the distribution network's overall voltage stability, is a novel metric proposed in this paper. This statistic can help distribution system operators make well-informed decisions about where and how big of DERs to put in order to increase the network's voltage stability. Overall, this paper makes a substantial contribution to the field of power system engineering by offering a more thorough and accurate examination of the effect of DRAL on the voltage stability of distribution networks in the smart grid.

2. Proposed system

The term "microgrid voltage stability" describes a microgrid's capacity to keep its distribution network's voltage level constant and tolerable. Ensuring that the energy provided to the associated loads is within safe and acceptable limits makes it a crucial component of microgrid operations. Keeping the voltage stable in a microgrid is mostly about giving the associated loads a dependable and effective energy source. Microgrids are extremely vulnerable to variations in energy production because the majority of them are linked to renewable energy sources like solar and wind power. These variations may have a substantial effect on the microgrid's voltage level.

Equation implies that larger values of exceeding voltage would result in the release or absorption of greater active power, thereby facilitating the mitigation of voltage excess. The droop coefficients α and β are determined by the maximum PV power $P_{PV}^{\max}$, maximum load power $P_{L}^{\max}$, and node rated voltage V_n^{rated} as.

$$\alpha = \frac{P_{PV}^{\max} - P_{L}^{\max}}{V_n^{\max} - V_n^{rated}} \tag{1}$$

$$\beta = \frac{P_{PV}^{\max} - P_{L}^{\max}}{V_n^{rated} - V_n^{\min}} \tag{2}$$

In addition, the active power of droop control P_n^{droop} can also be expressed by the ESS state of charge (SOC) variation,

$$P_n^{droop} = \frac{E_n \Delta SOC_{n,t}}{\Delta t} \tag{3}$$

where $\Delta SOC_{n,t}$ is the variation of SOC; E_n is the nth ESS's capacity; Δt denotes the charging or discharging time.

A microgrid's voltage strength is influenced by various elements such as the nature of the connected loads, the size and kind of renewable energy sources, and the energy storage capacity that is available. Microgriad managers use a range of methods and approaches, including as energy storage management, load shedding, and the monitoring and control of energy sources, to ensure voltage stability. Load shedding is one of the main techniques for microgrid voltage stability. Load shedding is a technique used to regulate the energy supply-demand ratio by momentarily disconnecting some loads from the microgrid. The microgrid controller recognizes the essential loads and disconnects them if the voltage level is outside of the allowable range. This can be done manually or automatically.

- **Line of Study**

Line of study, or study lines, refer to the significant subject areas studied in an educational program. These lines of study are organized into a curriculum designed to give students a thorough understanding and knowledge of a particular field. They are intended to guide students in their learning journey and serve as a framework for their academic progress. The operations of the line of study involve identifying and selecting a specific field of study, such as mathematics, science, history, or business. The structure diagram has shown in the following fig.1

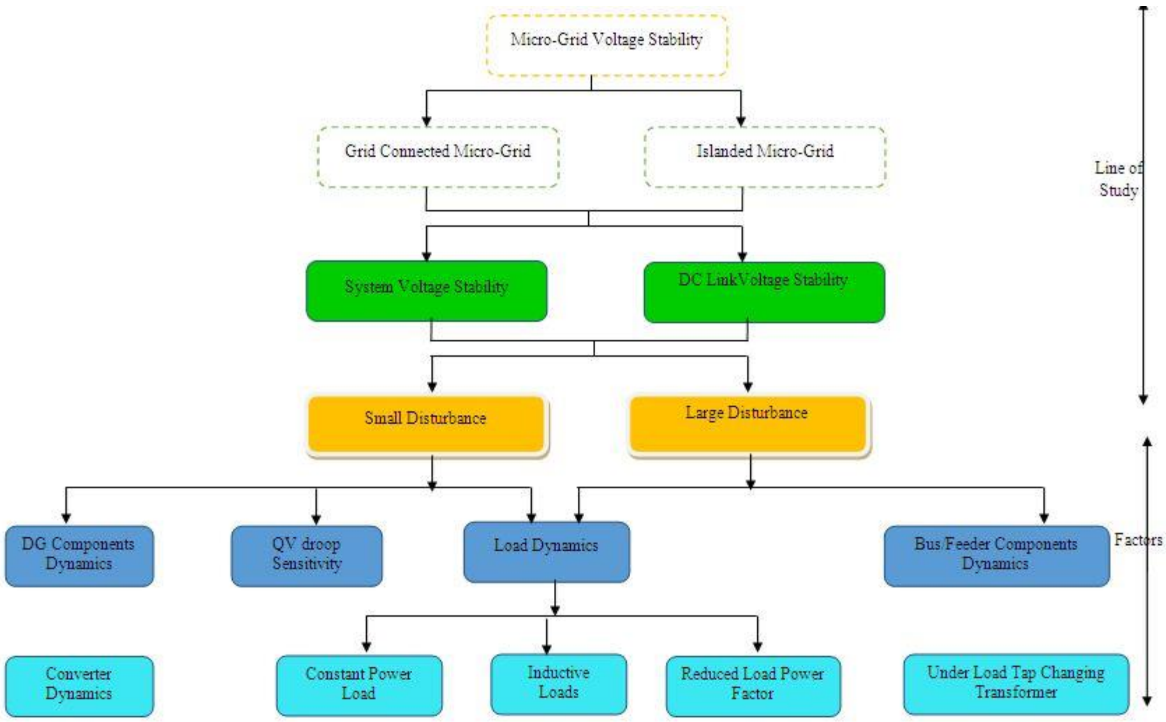

Fig 1: structure diagram

This decision is usually based on the student's interests, skills, and career aspirations. Once the line of study is chosen, students are directed toward a set of courses that will provide them with the fundamental knowledge and skills required for that particular field. Each line of study has unique learning goals and outcomes aligned with the educational program's overarching goals. These goals serve as a roadmap for students to follow and provide a clear direction for their academic journey. They also help students understand the importance of each course and how it contributes to their overall understanding of the subject. As students progress through their studies, they are exposed to various topics and concepts that build upon one another. This scaffolding approach allows students to understand the subject matter and its applications better.

- **Factor**

Factors refer to the individual elements or variables that contribute to the outcome of a specific process or situation. These factors can be internal and external, and their presence or absence can significantly affect the operation. One of the critical operations of factors is their influence on decision-making. When faced with a complex problem or task, individuals or organizations often consider various factors before deciding. These factors include personal opinions, past experiences, financial implications, resource availability, and potential risks. Each factor is crucial in shaping the final decision and its success. Factors also play a significant role in risk assessment and management. In any situation, various factors can increase or decrease the likelihood of a specific outcome.

When SOC variation is used as the control variable, the SOC relationship between different nodes possessing communication connections can be mathematically characterized, provided that the communication topology adheres to a strongly connected graph as follows

$$SOC_j[T+1] = \sum_{i \in \{N_j\} U \{j\}} A_{ij} SOC_j[T] \quad (4)$$

where N_j indicates the set of neighbors of node j ; $i \in \{N_j\} U \{j\}$ indicates that i is the

The convergence speed of distributed control is improved, and the flexibility of system operation is enhanced by optimizing the communication topology at the planning stage.

Minimize Total System Cost.

$$f_{CPDS}^{inv} = f_{ESS}^{inv} + f_{STU}^{inv} + f_{ESS}^{op} + f_{net}^{loss} + f_{PV}^{loss} + f_{EENS}^{loss} \quad (5)$$

Investment Cost

$$f_{ESS}^{inv} = \frac{d\left(1+d\right)^{y_1}}{\left(1+d\right)^{y_1} - 1} \sum_{m=1}^{M} E_m C_{ESS}^{inv} \tag{6}$$

$$f_{STU}^{inv} = \frac{d\left(1+d\right)^{y_2}}{\left(1+d\right)^{y_2} - 1} K C_{STU}^{inv} \tag{7}$$

These factors are carefully evaluated through risk assessment, and their potential impact is determined. This information is then used to develop risk management strategies to mitigate possible adverse outcomes. Factors also play a fundamental role in forecasting and planning. By analyzing various factors, such as market trends, consumer behavior, and economic conditions, organizations can make informed predictions and plan accordingly. These factors can also help identify potential opportunities or threats, allowing for proactive decision-making. Another vital operational factor is project management. Before starting a project, factors such as budget, team dynamics, and deadlines are carefully considered to ensure the successful completion of the project.

B. Functional working model

- **Medium Voltage Grid Control**

Medium Voltage Grid Control is a crucial element in controlling and managing the electrical grid. It refers to the various methods and technologies used to monitor, protect, and control the medium voltage (MV) network, which typically operates between 1kV and 33kV. One of the primary functions of Medium Voltage Grid Control is to ensure the energy flow in the MV network remains within safe and optimal limits. It is achieved through various control devices such as switches, fuses, circuit breakers, and protective relays. These devices are strategically placed throughout the network.

The spatial-temporal migration of their data loads is considered, without considering the investment costs of IDCs and corresponding servers.

$$f_{ESS}^{op} = 365 \sum_{t=1}^{T} \sum_{m=1}^{M} C_{ESS}^{unit} \left| P_{ESS}^{m,t} \right| \Delta T \tag{8}$$

T is the sample interval. The ESS's operational costs are translated into an equivalent yearly cost.ΔT is the total number of times that the battery has been charged and discharged, and $f_{IDC}^{op} = 365 \sum_{t=1}^{T} \sum_{r=1}^{\rho} D_{r,t} MP_t P_{IDC}^{t} \Delta T$

(9)

where MP_t denotes the marginal price of the distribution network at time t assuming the same price for each node in the distribution network.

$$f_{net}^{loss} = 365 \sum_{t=1}^{T} MP_t P_{loss}^{t} \Delta T \tag{10}$$

where P_{loss}^{t} is the network loss in period t,

$$f_{PV}^{loss} = 365 \sum_{t=1}^{T} \sum_{n=1}^{N_k} MP_t \left(P_{PV}^{n,t,\max} - P_{PV}^{n,t} \right) \Delta T \tag{11}$$

where $P_{PV}^{n,t,\max}$ denotes the maximum active power consumption of the distributed PV at node n in period t. $P_{PV}^{n,t}$ denotes the actual active power consumption; and N_k denotes the number of distributed PVs in the distribution network.

They preserve quickly isolate any faults or disturbances in the system to prevent them from spreading and causing power outages or damage to equipment. They can also help redirect the energy flow to maintain the grid's stability and avoid overloading. Medium Voltage Grid Control also involves advanced monitoring and communication technologies. Control centers then analyze and process this data, allowing operators to detect any abnormalities or potential issues in the MV grid. It enables them to take proactive measures to prevent disruptions and ensure the efficient operation of the network. Another crucial aspect of Medium Voltage Grid Control is load management.

- **Low Voltage Grid Control**

Low Voltage Grid Control, also known as LVGC, is a system that monitors and controls the electricity flow within a low-voltage power grid. This grid typically delivers power to residential, small commercial, and industrial areas. Its main objective is to ensure the safe and efficient operation of the grid by managing voltage levels and providing a stable supply of electricity to customers.

$$f_{EENS}^{loss} = 365\sum_{t=1}^{T}\sum_{n=1}^{N} P_{EENS}^{n,t} MP_t \Delta T \tag{12}$$

An EV user that needs to charge has the flexibility of charging at the available charging spot on the CS of choice, considering the following factors: the distance to the CS, the charging price of each CS, and the CS availability. The charging station's load l_t^{CS} at time t is given by

$$l_t^{CS} = \sum_{i=1}^{n} S_{i,t} . l_{S_{i,t}} , \tag{13}$$

$$y_t = \sum_{i=1}^{m} l_{i,t}^{CS} . \tag{14}$$

The load can be approximated with the Gaussian mixture model (GMM). Gaussian component densities can be combined with a weighted sum to form a GMM .In general, GMM can be expressed as follows

$$\wedge\left(r \middle| \mu_i, \Sigma_i, w_i\right) = \sum_{i=1}^{j} w_i \lambda\left(r \middle| \mu_i, \Sigma_i\right) \tag{15}$$

$$\lambda\left(r \middle| \mu_i, \Sigma_i\right) = \frac{1}{\left(2\pi\right)^{\frac{D}{2}} \left|\Sigma_1\right|^{\frac{1}{2}}} \exp - \frac{1}{2}\left(r-\mu_i\right)^T \Sigma_i^{-1}(r-\mu_i) \tag{16}$$

We further analyse the typical behaviour of vehicles commuting between residential and commercial areas in a day.

The first step in the operation of LVGC is the collection of data from the grid. It includes voltage levels, current flow, and power consumption. After that, this data is sent to a central control system for processing and analysis. The control system keeps an eye on the grid's condition and detects any possible problems or opportunities for improvement using sophisticated algorithms and predictive models. The functional block diagram is displayed in fig. 2.

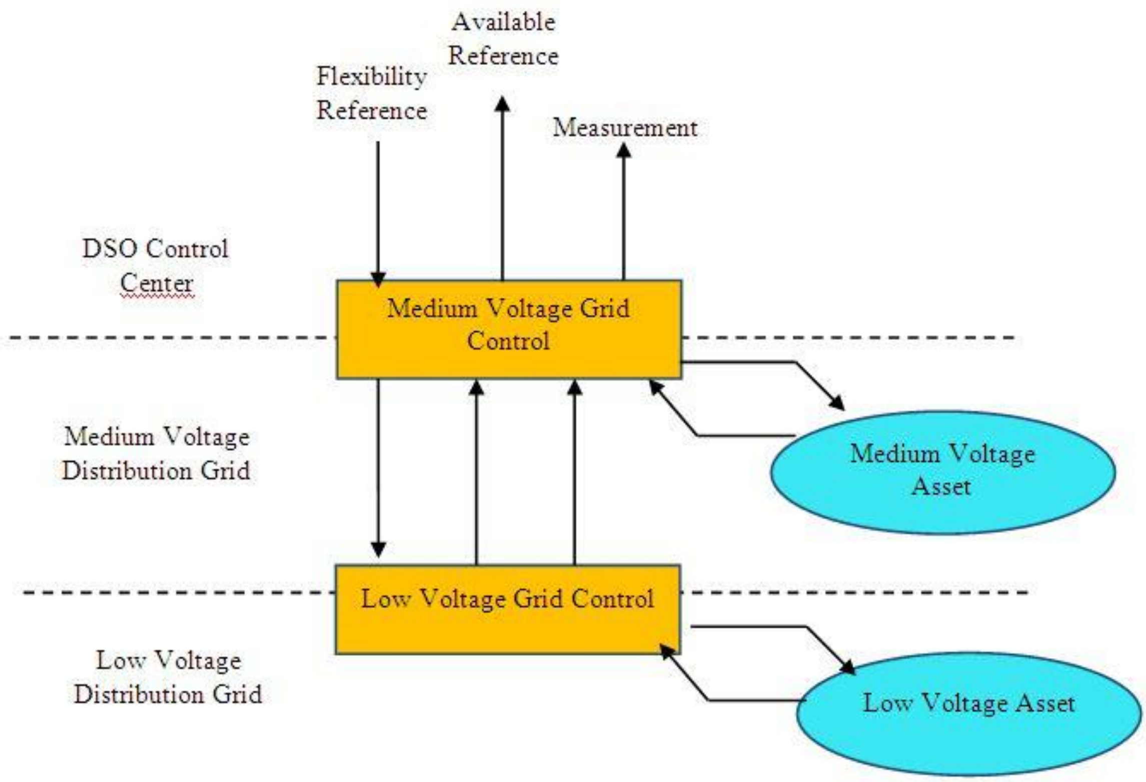

Fig 2: Functional block diagram

Once the data has been processed, the control system can make decisions and send commands to various devices and equipment on the grid. It can include switches, capacitors, and other control devices installed throughout the grid.

Let κ be the distribution network capacity and $x = (x_0, x_1, x_3, ..., x_{23})$ be the conventional load of the distribution network for 24 hours, sampled on an hourly interval. Evaluate x ′ with equation

$$x' = f(X) = 2 \times \frac{X}{\delta} - 1 \tag{17}$$

where f normalizes x in the range [1, −1] using δ and 0 as the maximum and minimum thresholds respectively.

find δ_1 and δ_2 using equations respectively, where $max(x')$ and $min(x')$ are the largest and the smallest element in x′ .

$$\delta_1 = 1 - \max(x') \tag{18}$$

$$\delta_2 = -1 - \min(x') \tag{19}$$

δ_1 and δ_2 addition to x′ is element-wise. y′ is the normalized desired load that must come from the charging of EVs. We denormalize y′ to get y using equation.

These devices help to regulate voltage levels, balance loads, and control the flow of electricity to different areas of the grid. A critical function of LVGC is voltage regulation. Voltage levels can fluctuate due to various factors, such as changes in demand, changes in power generation, or faults in the grid. LVGC maintains acceptable voltage levels by increasing or decreasing the voltage as needed.

- **Medium Voltage Asset**

A Medium Voltage (MV) asset refers to any electrical equipment or component that operates at voltage levels between 1kV and 72.5kV. These assets are used in power distribution systems to transmit electricity from high-voltage transmission lines to low-voltage distribution networks, providing electricity to homes, businesses, and industries. Some examples of MV assets include transformers, circuit breakers, switches, and protective relays.

$$y = f'(y') = \zeta \times (\frac{y'+1}{2}) \tag{20}$$

After obtaining the desired valley-filling load y, the charging price is computed in the following manner.
Power balance, branch currents, nodal voltages, and DG installation capacity are among the limitations. Plan and optimize the configuration strategy after that. $APL = f_1 = P_{loss} = \sum_{k=1}^{N_b} G_k \left(U_i^2 + U_j^2 - 2U_iU_j \cos\delta_{ij}\right)$

(21)

where is the phase angle between bus i and bus j, is the nodal voltage between bus i and bus j, is the conductance between bus i and bus j, and is the total branch number.

$$IOMC = f_2 = \sum_{k=1}^{N_d} x_i \left[\left(\frac{r(1+r)^n}{(1+r)^n - 1} . C_{D_i} + C_{ri}\right)\right] P_{DG_i} \tag{22}$$

where are the installed capacity, investment cost, and operating cost of the DG installed at node i; n is the number of years of planning; xi is the type of DG installed at bus i; and r is the annual rate of return, which is taken to be 0.1.

$$PPC = f_3 = \left(P_W - P_{\sum DG} - \Delta P_L\right) T_{\max} C_{p,u} \tag{23}$$

where PW stands for the system's total capacity, is the DG's total active output, is the active loss both before and after optimization, is the maximum number of hours that the load can be used annually, and is the cost of electricity.

$$VSM = f_4 = B = 1 - \max\{L_n\} \tag{24}$$

where B is the first type of voltage stability margin, The smaller $max\{L_1, L_2, \cdots, Ln\}$ is, the larger B is and the more stable the distribution network voltage is; the first type of voltage stability index L_{ij} for the branch between bus i, j is

The operation of MV assets involves a complex series of processes that ensure reliable and safe delivery of electricity to end-users. The first step in the operation of an MV asset is its installation and commissioning. It involves carefully selecting the location, setting up the equipment, and testing to ensure it functions correctly.

$$L_{ij} = 4\frac{\left(P_jX_{ij} - Q_jR_{ij}\right)^2 + \left(P_jR_{ij} + Q_jX_{ij}\right)V_i^2}{V_i^4} \tag{25}$$

n Considering that each sub-objective function has different magnitudes and conflicts with each other, it is difficult to reach the optimization at the same time, so it needs to be dimensionless

$$f* = \frac{f - f_{\min}}{f_{\max} - f_{\min}} \tag{26}$$

$$F = \omega_1 f_1^* + \omega_2 f_2^* + \omega_3 f_3^* + \omega_4 f_4^* \tag{27}$$

where ω_i are weighting factors, ω_1=0.3, $\omega_2 = 0.2, \omega_3 = 0.3, \omega_4 = 0$

The installation process also involves incorporating additional safety features, such as grounding and protective devices, which are crucial for the asset's overall performance. Once the MV asset is installed, it becomes an integral part of the power distribution system. Controlling and regulating the flow of electricity within the network is its main duty.

The conductance and conductance between bus i and j are the real and imaginary components of the voltage at bus i.

$$U_{i\min} \le U_i \le U_{i\max} \tag{28}$$

where, $U_{i\min}$ and $U_{i\max}$ are the upper and lower limits of voltage at bus i.

$$I_{ij} \le I_{ij\max} \tag{29}$$

where $I_{ij\max}$ is the maximum current allowed for the branch.

$$\sum P_{DG} \le \eta \sum P_{Load} \tag{30}$$

It is typically achieved through control and monitoring devices, which constantly measure the voltage, current, and other system parameters. Based on these measurements, the assets can automatically switch on or off, adjust voltages, and protect against overloads or faults to maintain a stable flow of electricity.

- **Low Voltage Asset**

Low Voltage Asset refers to electrical equipment or system operating at a relatively low voltage level, typically below 1 kV. These assets are crucial in delivering electricity to end-users in residential, commercial, and industrial settings. The primary function of Low Voltage Assets is to transform and distribute electric energy from high-voltage transmission lines to the devices and appliances that require it for operation. The process involves stepping down the high-voltage electricity (typically 110 kV to 400 kV) to a lower voltage, which is distributed through power lines to the end users. At the heart of a Low Voltage Asset is a transformer, an electromagnetic device that converts electrical energy from one voltage level to another.

The balance factor, which is described as, determines when BWO is transferred from the exploration to the exploitation phase.

$$B_f = B_0\left(1 - T / 2 * T_{\max}\right) \tag{31}$$

where is a random value between 0 and 1 at each iteration; when > 0.5, the algorithm is in the exploration phase. T and are the current and maximum iteration numbers.

when $B_f \le 0.5$, the algorithm is in the exploitation,

$$\begin{cases} X_{ij}^{T+1} = X_{i,pj}^{T} + \left(X_{r,pr}^{T} - X_{i,pi}^{T}\right), j = even \\ X_{ij}^{T+1} = X_{i,pj}^{T} + \left(X_{r,pr}^{T} - X_{i,pi}^{T}\right), j = odd \end{cases} \tag{32}$$

The beluga whale's new location inside the dimension is indicated by a random number between [1, D] and.

The transformer operates on the basis of electromagnetic induction, in which a current is induced in the secondary winding by a magnetic field created by an alternating current (AC) flowing through the primary winding. After the voltage is reduced, the electricity travels via a system of switchgear, transformers, and distribution lines. Distribution lines are usually subterranean or overhead cables that deliver electricity to the final consumers. The distribution transformers further reduce the voltage to a safe and usable level, normally 230/415 volts for residential and commercial settings.

- **Detection Stage**

The detection stage of a system is an essential part of the overall process. Its primary function is to accurately identify and locate potential threats or anomalies within a given environment. This stage is crucial because it provides a foundation for the subsequent stages of the system, such as mitigation and response. In this stage, the system uses various techniques and algorithms to detect suspicious behaviour, patterns, or events and classify them as a potential threat.

Based on the odd or even dimension of the current iteration, the positions of the and beluga whale indicate that the whale is swimming in a mirror or synchronized manner.

$$X_i^{T|+1} = r_3 X_{best}^T - r_4 X_i^T + C_1.L_F.\left(X_r^T - X_i^T\right) \tag{33}$$

The Levy flying strategy's random leap strength is determined by where beluga whales are most likely to be found, their current positions, and their optimal positions.

$$L_F = 0.05 \times \frac{u \times \sigma}{|v|^{1/\beta}} \tag{34}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\pi\beta/2)}{\Gamma((1+\beta)/2) \times 2^{(\beta-1)/2}} \right)^{1/\beta} \tag{35}$$

The step factor of whale fall, W_f is the probability of whale fall, which is defined as:

$$W_f = 0.1 - 0.05T / T_{\max} \tag{36}$$

The first step in the detection stage is gathering data from various system sources. This data can include network traffic, system logs, user activities, and other relevant information. Anomaly detection algorithms are applied to this data to identify unusual or suspicious activity. The operational flow diagram has shown in the following fig.3

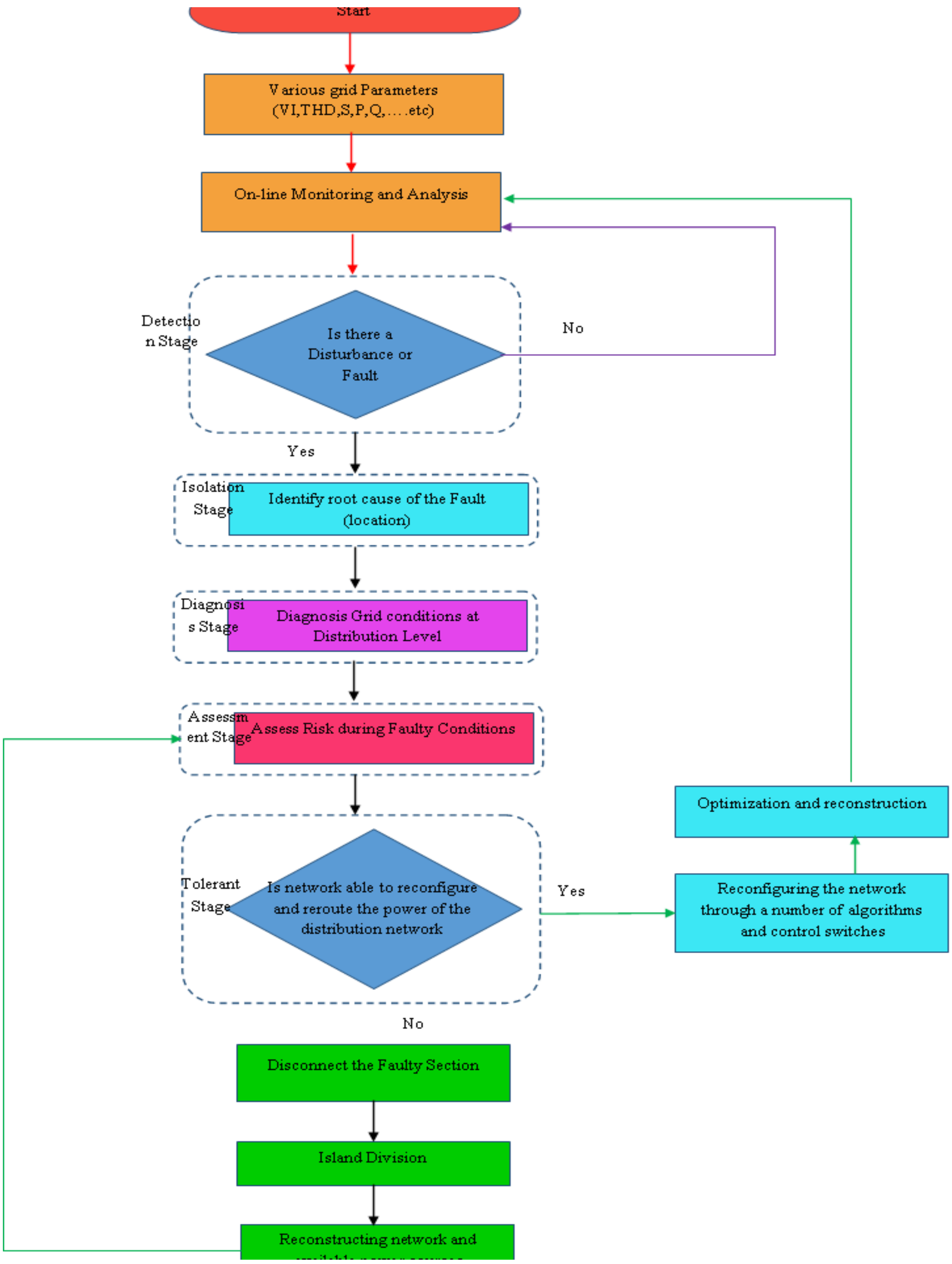

Fig 3: Operational flow diagram

This algorithms use statistical methods, machine learning, and other techniques to detect deviations from normal behaviour that may indicate a potential threat. One of the critical techniques used in the detection stage is signature-based detection. This approach compares new data with known patterns or signatures of threats. The system can flag the activity as malicious if a match is found. This method is effective in identifying known and previously identified threats. However, it may be less effective in detecting new or unknown threats. Behaviour-based detection techniques are also used in the detection stage to address this limitation.

- **Isolation Stage**

The Isolation Stage is a critical component in database management systems (DBMS), ensuring data reliability and consistency during concurrent operations. It is responsible for isolating and controlling the interactions between different transactions, or units of work, that are being executed in the database. The main objective of the isolation stage is to prevent the so-called "dirty reads," where a transaction reads uncommitted data from another transaction that has not yet been fully completed. It can lead to incorrect or inconsistent data accessed by other transactions, seriously affecting the database.

The algorithm may leave the local optimum by introducing the EOBL approach at the start of each iteration, which can broaden the search space and boost population diversity. It can be articulated as follows:

$$\overline{X_{i,j}^{e}} = K*\left(\alpha_j + \beta_j\right) - X_{i,j}^{e} \tag{37}$$

Consequently, in order to improve the BWO's exploration and development phases, iterative modification is carried out.

$$B_f = B_{f\min} + \left(B_{f\min} - B_{f\max}\right).\exp\left(In\frac{B_{f\min}}{B_{f\max}}.\frac{T}{T_{\max}}\right) \tag{38}$$

The cyclone foraging technique in the MRFO is implemented to improve the BWO's development phase even more. The revised equation for the enhanced phase of exploitation

$$\beta = 2e^{r_9\frac{T-t+1}{T}}.\sin\left(2\pi r_9\right) \tag{39}$$

The Isolation Stage employs techniques and controls to achieve this, collectively known as the isolation levels. These levels determine the degree of interaction and data visibility between concurrent transactions. At the lowest level, Read Uncommitted, there is no isolation between transactions, and any transaction can read uncommitted data from another transaction. This level provides the highest level of concurrency but also the lowest data consistency. At the other end of the spectrum, the serializable level offers the highest level of data consistency by preventing concurrent transactions from modifying data being read or written by another transaction. This level, however, limits concurrency and can result in performance issues.

- **Diagnosis Stage**

The Diagnosis Stage is a crucial part of diagnosing any disease or illness. It is the step in the medical process where doctors and healthcare providers utilize various diagnostic tests, patient evaluations, and medical histories to accurately identify patients' underlying medical conditions. The gateway in the Diagnosis Stage is for the doctor to take a thorough remedial history, which includes collecting information about the patient's symptoms, previous medical conditions, and any family history of diseases.

The analytical line stability index, NVSP, was formulated from two-bus-reduced power network grid as shown inThe current $\left(I\right)$ from the PV bus 1 can be calculated as

$$I = \left(V_1 - V_2\right).Y_{bus} \tag{40}$$

Then load current at the PQ bus (i.e. bus 2) could be expressed as:

$$I = \left(\frac{S_2}{V_2}\right) = \frac{P_2 - jQ_2}{V_2\angle-\delta_2} \tag{41}$$

The real part of equation could be expressed as

$$\frac{4P_2}{G\cos\theta.\left|V_1\right|^2\cos^2\left(-\delta_2\right)} \le 1 \tag{42}$$

The STATCOM which is a voltage source converter was connected with a shunt direct current (dc) capacitor. The controllable AC output voltage, $V_o(t)$, from generated by the converter is given by equation

$$V_o(t), V_o \sin(\omega - \delta) \tag{43}$$

where V_o and δ denote the STATCOM voltage and phase angle, respectively.

Similarly, when the V_s and V_o are in phase, there would be no action performed by the controller, hence, it will be dumb or idle. In addition, the STATCOM is designed to be controlled by two signals which are phase angle δ and magnitude, k given by

$$\overline{V_o} = kV_{dc}(\cos\delta + j\sin\delta) = kV_{dc}D\delta \tag{44}$$

$$\overline{I_{ao}} = I_{aod} + I_{aoq} \tag{45}$$

where m denotes the modulation index of the pulse width modulation (PWM).

This step is essential as it allows the doctor to gather valuable information to help guide the diagnostic process. The next step is for the doctor to examine the patient physically. The doctor will also assess the patient's overall appearance, including skin colour, muscle strength, and coordination, which can provide valuable clues about the patient's condition. The doctor may order specific diagnostic tests following the physical examination to gather more information about the patient's condition. These tests can include blood tests, imaging scans like X-rays or MRIs, or other more invasive procedures like biopsies. The results of these tests play a crucial role in helping the doctor form a diagnosis.

- **Assessment Stage**

The Assessment Stage is essential to the operational process in various industries and organizations. This stage involves evaluating data and information collected from previous stages to determine the effectiveness and efficiency of the overall process. The main seek of the Assessment Stage is to classify any areas for improvement and make necessary changes to increase productivity and achieve the desired outcomes. The first step in the Assessment Stage is the collection of data from the execution stage. This data may include measurements, observations, feedback, and other relevant information.

The power flow mathematical expressions with an installed STATCOM are given by equations

$$P_m = P_{sh} + \sum_{j=1}^{N} |V_m||V_j||Y_{mj}|\cos(\theta_{mj} - \delta_{mj}) \tag{46}$$

$$Q_m = Q_{sh} + \sum_{j=1}^{N} |V_m||V_j||Y_{mj}|\sin(\theta_{mj} - \delta_{mj}) \tag{47}$$

In this settings, the reactive power (Qs) of all the generators, but slack bus generator, in the power grid and voltages of all generator buses (V_s) act as controlling parameters.

This data is then analyzed to determine the performance of the process and any possible deviations from the expected results. Once the data has been analysed\, the next step is to interpret the findings. It involves comparing the actual results with the predetermined goals and objectives. This comparison helps to identify any gaps or deficiencies in the operational process. It also helps to determine whether the objectives were achieved within the set timeline and budget. The next step is identifying the root causes of any issues or problems identified during the assessment. It involves a more detailed examination of the data and information collected. After identifying the root causes, the next step is to formulate recommendations for improvement.

- **Tolerant Stage**

The Tolerant Stage is an essential part of many systems' overall data processing pipeline. IVarious techniques are utilized in this stage to handle data abnormalities and inconsistencies, allowing for more robust data processing. Three primary operations are carried out in the Tolerant Stage: data profiling, data cleansing, and data transformation. This operation involves analysing and understanding the various data sources being processed. It is a critical step in identifying potential data issues, such as missing values, duplicate entries, or invalid data types. Profiling techniques include statistical analysis, data sampling, and pattern recognition to gain insights into the data and its quality. Once data profiling is complete, cleaning the data is followed. This operation involves detecting and removing any corrupt, incomplete, or irrelevant data. It is done by applying various data-cleaning techniques such as deduplication, normalization, and validation. For example, duplicate entries are removed in data deduplication, ensuring data consistency and accuracy. The final operation in the Tolerant Stage is data transformation. It involves converting the data from its original format into a more suitable and valuable format for downstream processing. It can include merging different data sources, aggregating data, or performing calculations. For instance, data transformation can combine customer information from multiple databases into one cohesive dataset for further analysis.

4. Result and Discussion

The performance of proposed method Distributed Resource Access Location and Capacity Analysis (DRALC) have compared with Voltage Stability of Distribution Networks (VSDN), Comprehensive Distributed Resource Access (CDRA) and Distributed Energy Resources (DER).

4.1. Voltage stability margin

This parameter measures the distance among the actual voltage levels in the circulation network and the voltage threshold at which voltage collapse occurs. A higher voltage stability margin indicates a more stable and reliable network, while a lower margin indicates a higher risk of voltage instability. Table.2 shows the evaluation of Voltage stability margin between existing and proposed models.

Table.2: evaluation of Voltage stability margin (in %)

No. of Images	VSDN	CDRA	DER	DRALC
100	88.02	87.14	97.19	98.82
200	86.28	85.56	95.77	97.53
300	83.94	83.36	94.51	96.52
400	83.13	81.73	92.52	95.63
500	80.84	80.59	90.05	95.26

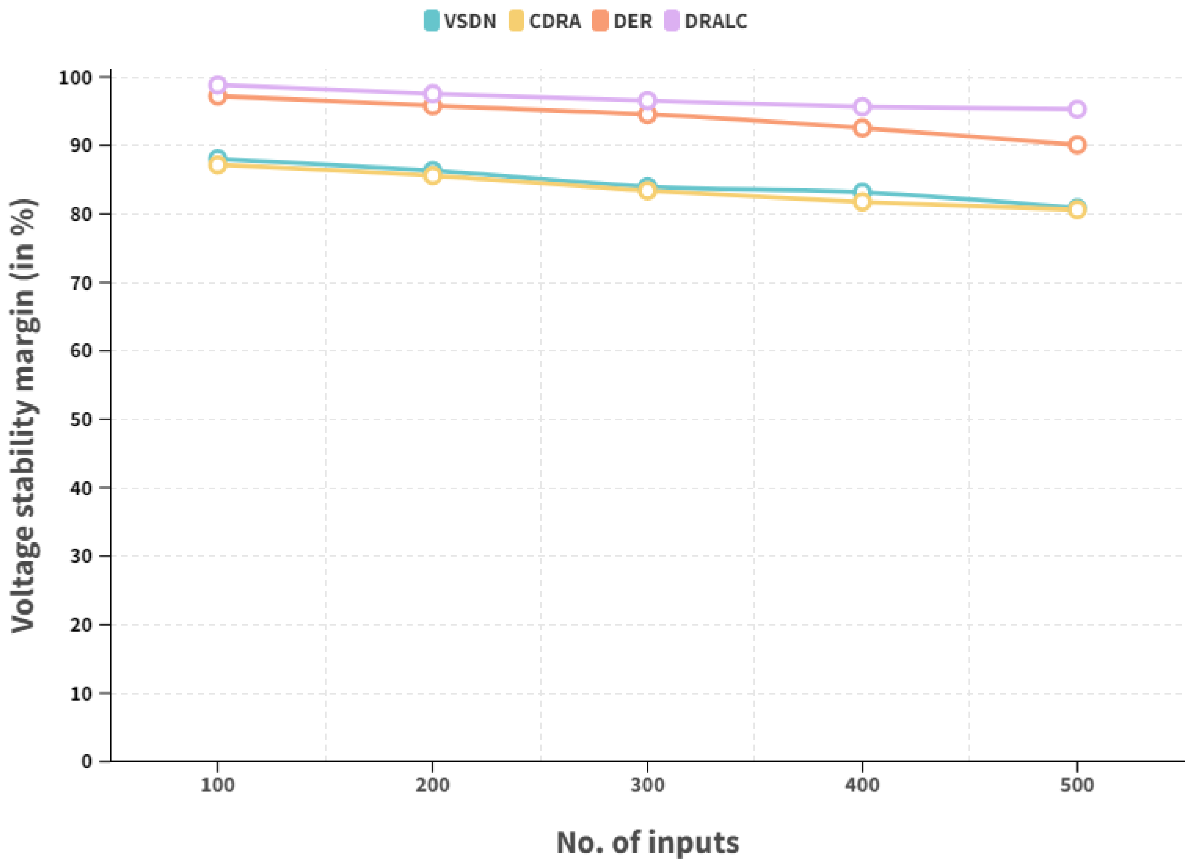

Fig.4: evaluation of Voltage stability margin

Fig. 4 shows the evaluation of Voltage stability margin. In a computation cycle, the existing VSDN obtained 80.84 %, CDRA obtained 80.59%, DER reached 90.05 % Voltage stability margin. The proposed DRALC obtained 95.26% Voltage stability margin.

4.2. Distributed resource capacity

This refers to the maximum amount of distributed resources that can be connected to the distribution network without causing voltage stability issues. It takes into account the technical characteristics of the distributed resources, such as their voltage and reactive power capabilities, as well as the network's load and topology Table.3 shows the evaluation of resource capacity between existing and proposed models.

Table.3: evaluation of resource capacity (in %)

No. of Images	VSDN	CDRA	DER	DRALC
100	86.02	89.14	92.19	94.82
200	84.28	87.56	90.77	93.53
300	81.94	85.36	89.51	92.52
400	81.13	83.73	87.52	91.63
500	78.84	82.59	85.05	91.26

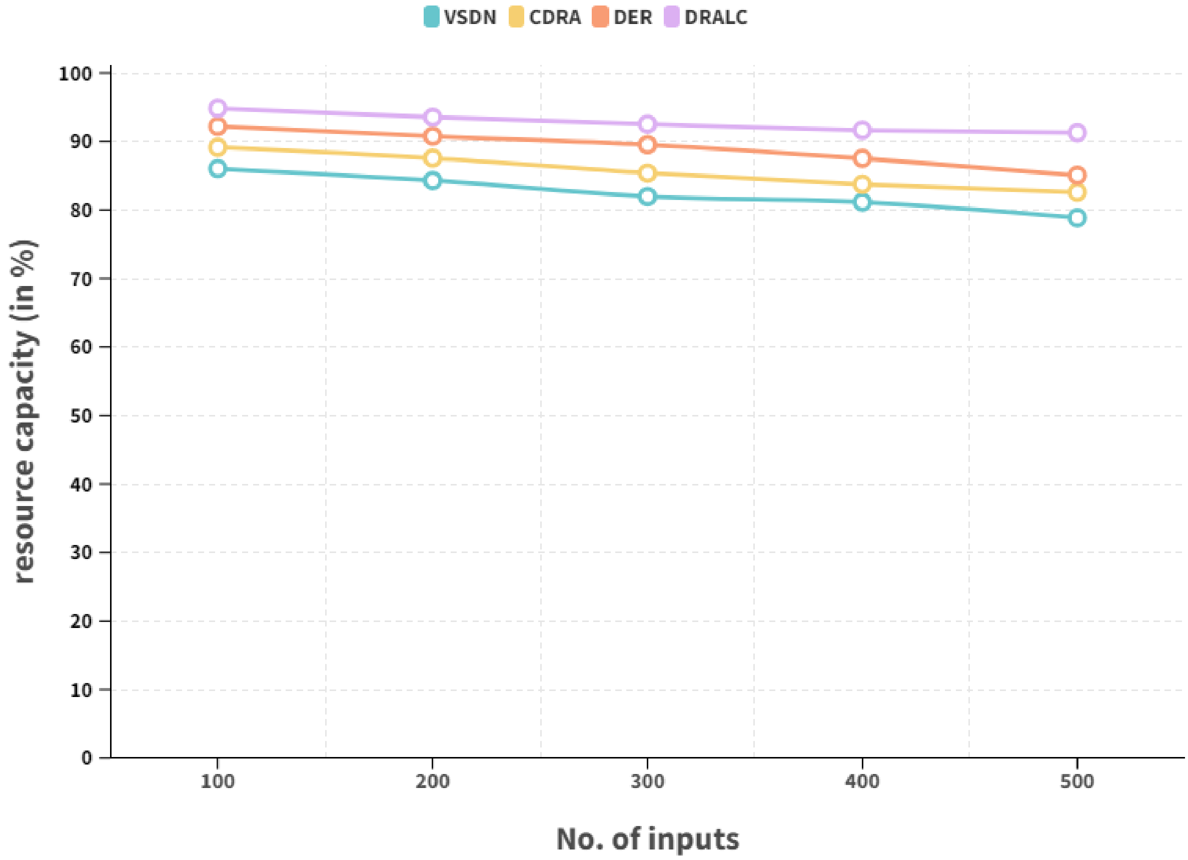

Fig.5: assessment of resource capacity

Fig. 5 shows the assessment of resource capacity . In a computation cycle, the existing VSDN obtained 78.84 %, CDRA obtained 82.59 %, DER reached 85.05% resource capacity. The proposed DRALC obtained 91.26 % resource capacity.

4.3. Location of distributed resources

The geographical distribution of distributed resources plays a vital role in determining their impact on voltage stability. The technical performance parameter, in this case, would be the optimal location of distributed resources that minimizes voltage deviations and maximizes stability in the distribution network. Table.4 shows the assessment of distributed resources between existing and proposed models.

Table.4: assessment of distributed resources (in %)

No. of Images	VSDN	CDRA	DER	DRALC
100	82.02	87.14	89.19	92.82
200	80.28	85.56	87.77	91.53
300	77.94	83.36	86.51	90.52
400	77.13	81.73	84.52	89.63
500	74.84	80.59	82.05	89.26

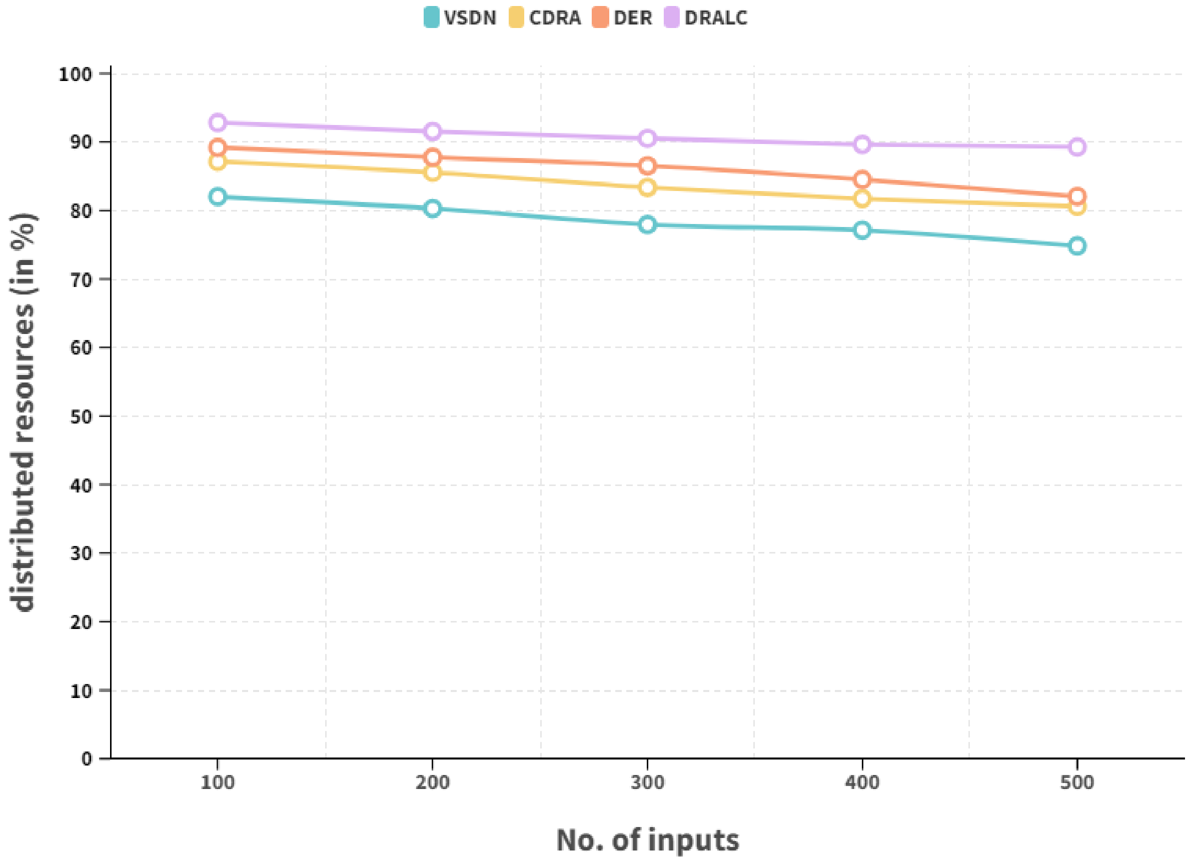

Fig.6: Comparison of distributed resources

Fig. 6 shows that the comparison of distributed resources . In a view cycle, the existing VSDN obtained 74.84 %, CDRA obtained 80.59%, DER reached 82.05 % distributed resources. The proposed DRALC obtained 89.26 % distributed resources.

4.4. Access control mechanisms

The access control mechanisms for distributed resources determine the level of control and coordination between the resources and the distribution network. This parameter includes aspects such as communication protocols, control algorithms, and coordination strategies, which all have a direct impact on the voltage stability of the network. Table.5 shows the evaluation of Access control mechanisms among existing and proposed models.

Table.5: evaluation of Access control mechanisms (in %)

No. of Images	VSDN	CDRA	DER	DRALC
100	78.02	83.14	85.19	86.82
200	76.28	81.56	83.77	85.53
300	73.94	79.36	82.51	84.52
400	73.13	77.73	80.52	83.63
500	70.84	76.59	78.05	83.26

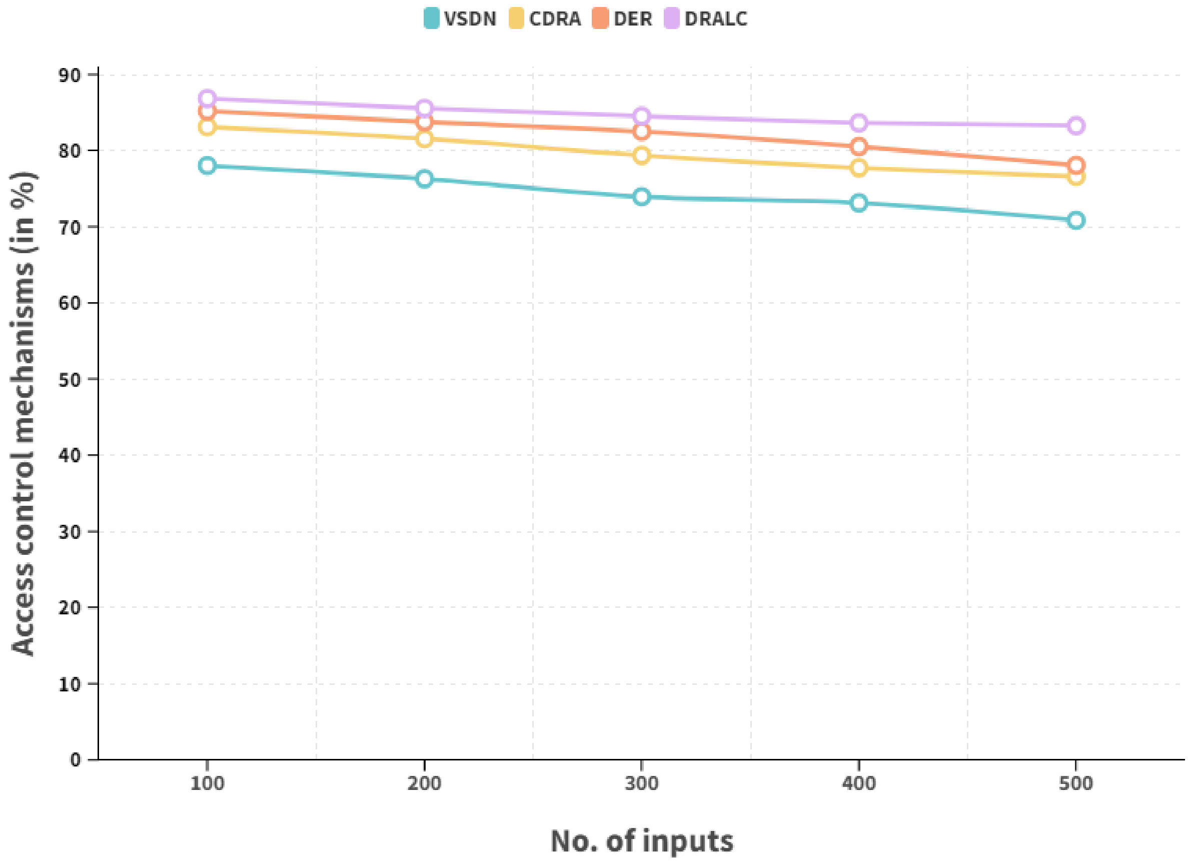

Fig.7: assessment of Access control mechanisms

Fig. 7 shows the assessment of Access control mechanisms . In a calculation cycle, the obtainable VSDN obtained 70.84%, CDRA obtained 76.59%, DER reached 78.05% Access control mechanisms. The proposed DRALC obtained 83.26 % Access control mechanisms.

5. Conclusion

Overall, the improved analysis conducted on the impact of Distributed Resource Access Location and Capacity (DRALC) on voltage stability of distribution networks in smart grid has shown that the integration of distributed resources can have both beneficial and detrimental effects on voltage stability. The location of distributed resources plays a crucial role in voltage stability, with strategic placement leading to improved stability, while poor placement can result in voltage collapse. Additionally, the capacity of these resources must be carefully managed to prevent overloading and voltage fluctuations. Therefore, careful consideration and optimization of DRALC is necessary for ensuring stable and efficient operation of smart grid distribution networks.

Acknowledgements

This work is supported by the China Southern Power Grid Science and Technology Project . Project name: Research and demonstration of multi-time scale adaptive whole-area distribution network self-healing technology considering distributed resource carrying capacity- Topic 3: Research on the Carrying Capacity of Distribution Networks for Distributed Resources and Optimization Control Technologies. Project number: GZKJXM20222431

References

[1] Arnold, D., Saha, S., Ngo, S. T., Roberts, C., Scaglione, A., Johnson, N. G., ... & Pinney, D. (2022). Adaptive control of distributed energy resources for distribution grid voltage stability. IEEE Transactions on Power Systems, 38(1), 129-141.

[2] Shaheen, A. M., El-Sehiemy, R. A., Kamel, S., Elattar, E. E., & Elsayed, A. M. (2021). Improving distribution networks' consistency by optimal distribution system reconfiguration and distributed generations. IEEE Access, 9, 67186-67200.

[3] Alanazi, M. S. (2022). A MILP model for optimal renewable wind DG allocation in smart distribution systems considering voltage stability and line loss. Alexandria Engineering Journal, 61(8), 5887-5901.

[4] Huang, W., Zheng, W., & Hill, D. J. (2021). Distribution network reconfiguration for short-term voltage stability enhancement: An efficient deep learning approach. IEEE Transactions on Smart Grid, 12(6), 5385-5395.

[5] Adewuyi, O. B., Adeagbo, A. P., Adebayo, I. G., Howlader, H. O. R., & Sun, Y. (2021). Modified analytical approach for PV-DGs integration into a radial distribution network considering loss sensitivity and voltage stability. Energies, 14(22), 7775.

[6] Boričić, A., Torres, J. L. R., & Popov, M. (2021). Fundamental study on the influence of dynamic load and distributed energy resources on power system short-term voltage stability. International Journal of Electrical Power & Energy Systems, 131, 107141.

[7] Li, Q., Zhou, F., Guo, F., Fan, F., & Huang, Z. (2021). Optimized energy storage system configuration for voltage regulation of distribution network with PV access. Frontiers in Energy Research, 9, 641518.

[8] Gholami, K., Karimi, S., Rastgou, A., Nazari, A., & Moghaddam, V. (2024). Voltage stability improvement of distribution networks using reactive power capability of electric vehicle charging stations. Computers and Electrical Engineering, 116, 109160.

[9] Pillai, S. E. V. S., & Hu, W. C. (2023, May). Misinformation detection using an ensemble method with emphasis on sentiment and emotional analyses. In 2023 IEEE/ACIS 21st International Conference on Software Engineering Research, Management and Applications (SERA) (pp. 295-300). IEEE

[10] Meena, A., Reddy, G. V., & Chavali, D. P. (2024, March). Accelerated CNN Training with Genetic Algorithm. In 2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI) (Vol. 2, pp. 1-6). IEEE.

[11] Adetunji, K. E., Hofsajer, I. W., Abu-Mahfouz, A. M., & Cheng, L. (2022). An optimization planning framework for allocating multiple distributed energy resources and electric vehicle charging stations in distribution networks. Applied Energy, 322, 119513.

[12] Gupta, P., & Verma, Y. P. (2021). Voltage profile improvement using demand side management in distribution networks under frequency linked pricing regime. Applied Energy, 295, 117053.

[13] Rao, B. V., Stefan, M., Brunnhofer, T., Schwalbe, R., Karl, R., Kupzog, F., ... & Kozek, M. (2022). Optimal capacity management applied to a low voltage distribution grid in a local peer-to-peer energy community. International Journal of Electrical Power & Energy Systems, 134, 107355.

[14] Rahman, T., Xu, Y., & Qu, Z. (2021). Continuous-domain real-time distributed ADMM algorithm for aggregator scheduling and voltage stability in distribution network. IEEE Transactions on Automation Science and Engineering, 19(1), 60-69.

[15] Wu, Z. Z., Xu, Y. P., Cheng, Z. L., Sun, H. W., Papari, B., Sajadi, S. S., & Qasim, F. (2022). Optimal placement and sizing of the virtual power plant constrained to flexible-renewable energy proving in the smart distribution network. Sustainable Energy Technologies and Assessments, 49, 101688.

[16] Van Tran, T., Truong, B. H., Nguyen, T. P., Nguyen, T. A., Duong, T. L., & Vo, D. N. (2021). Reconfiguration of distribution networks with distributed generations using an improved neural network algorithm. IEEE Access, 9, 165618-165647.

[17] Akbar, M. I., Kazmi, S. A. A., Alrumayh, O., Khan, Z. A., Altamimi, A., & Malik, M. M. (2022). A novel hybrid optimization-based algorithm for the single and multi-objective achievement with optimal DG allocations in distribution networks. IEEE Access, 10, 25669-25687.

[18] Han, C., Lee, D., Song, S., & Jang, G. (2022). Probabilistic assessment of PV hosting capacity under coordinated voltage regulation in unbalanced active distribution networks. IEEE Access, 10, 35578-35588.

[19] Saidi, A. S. (2022). Impact of grid-tied photovoltaic systems on voltage stability of tunisian distribution networks using dynamic reactive power control. Ain Shams Engineering Journal, 13(2), 101537.

[20] Lee, J. W., & Kim, M. K. (2022). An Evolutionary Game theory-based optimal scheduling strategy for multiagent distribution network operation considering voltage management. IEEE Access, 10, 50227-50241.

[21] Ahmadi, M., Adewuyi, O. B., Danish, M. S. S., Mandal, P., Yona, A., & Senjyu, T. (2021). Optimum coordination of centralized and distributed renewable power generation incorporating battery storage system into the electric distribution network. International Journal of Electrical Power & Energy Systems, 125, 106458.

[22] Hassan, A. S., Othman, E. A., Bendary, F. M., & Ebrahim, M. A. (2022). Improving the techno-economic pattern for distributed generation-based distribution networks via nature-inspired optimization algorithms. Technology and Economics of Smart Grids and Sustainable Energy, 7(1), 3.

[23] Liu, D., Zeng, P., Cui, S., & Song, C. (2023). Deep reinforcement learning for charging scheduling of electric vehicles considering distribution network voltage stability. Sensors, 23(3), 1618.

[24] Mahmoud, K., & Lehtonen, M. (2021). Comprehensive analytical expressions for assessing and maximizing technical benefits of photovoltaics to distribution systems. IEEE Transactions on Smart Grid, 12(6), 4938-4949.

[25] Abideen, M. Z. U., Ellabban, O., Ahmad, F., & Al-Fagih, L. (2022). An enhanced approach for solar PV hosting capacity analysis in distribution networks. IEEE Access, 10, 120563-120577.

[26] Faraji, E., Abbasi, A. R., Nejatian, S., Zadehbagheri, M., & Parvin, H. (2021). Probabilistic planning of the active and reactive power sources constrained to securable-reliable operation in reconfigurable smart distribution networks. Electric Power Systems Research, 199, 107457.

[27] Zhan, H., Wang, J., Ding, Y., Lu, J., Cu, R., Tan, Q., & Lu, X. (2023, October). Research on Voltage Stability of Distributed Photovoltaic Active Distribution Network with High Permeability. In International Conference on Wireless Power Transfer (pp. 699-706). Singapore: Springer Nature Singapore.

[28] Haider, W., Hassan, S. J. U., Mehdi, A., Hussain, A., Adjayeng, G. O. M., & Kim, C. H. (2021). Voltage profile enhancement and loss minimization using optimal placement and sizing of distributed generation in reconfigured network. Machines, 9(1), 20.

[29] Rajagopalan, A., Swaminathan, D., Alharbi, M., Sengan, S., Montoya, O. D., El-Shafai, W., ... & Aly, M. H. (2022). Modernized planning of smart grid based on distributed power generations and energy storage systems using soft computing methods. Energies, 15(23), 8889.

[30] Li, Y., Feng, B., Wang, B., & Sun, S. (2022). Joint planning of distributed generations and energy storage in active distribution networks: A Bi-Level programming approach. Energy, 245, 123226.