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INSTITUTE OF ENGINEERING

PULCHOWK CAMPUS

THESIS NO: 076/MSPSE/004

Reliability Enhancement of Electric Distribution Network Using Optimal Placement of Distributed Generation: A Case Study of 33/11 KV Udipur Substation Distribution feeders, Lamjung.

by

Bibas Raj Acharya

A THESIS

SUBMITTED TO THE DEPARTMENT OF ELECTRICAL ENGINEERING

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR

THE DEGREE OF MASTER OF SCIENCE IN

POWER SYSTEM ENGINEERING

DEPARTMENT OF ELECTRICAL ENGINEERING

LALITPUR, NEPAL

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CERTIFICATE OF APPROVAL

The undersigned certify that they have read, and recommend to the Institute of Engineering for acceptance, a thesis entitled "**Reliability Enhancement of Electric Distribution Network Using Optimal Placement of Distributed Generation: A Case Study of the 33/11kV Udipur Substation Distribution feeders, Lamjung.**" submitted by **Mr. Bibas Raj Acharya** in partial fulfillment of the requirements for the degree of **Master of Science in Power System Engineering**.

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ABSTRACT

Reliability can be considered as the capability of system to survive. Currently, consumers are demanding reliable and cheaper power supply with reduced interruption duration. It's widely acknowledged that nearly 90% of electricity interruptions generates from faults within the electric distribution system. Distributed generation (DG) emerges as a novel solution, strategically locating power generation closer to where it's needed most—load centers. By adopting DG, we can effectively mitigate reliability challenges within distribution systems while fostering a more resilient and efficient energy delivery framework. The primary cause of customer service disruptions stems from faults within the distribution system, particularly on radial distribution feeder lines. Additional contributing factors include adverse weather conditions such as windy rain, incidents involving animals, and intrusion from tree branches. These various elements collectively contribute to interruptions in customer service. This study focuses on integrating Distributed Generation (DG) into distribution systems to assess its impact on reliability. Optimal placement of DG is a critical design consideration significantly influencing distribution system reliability. As the distance between load centers and feeders increases, outage durations also escalate. The introduction of Distributed Generation (DG) significantly enhances the reliability of power distribution systems. In the RBTS Bus-2 distribution system, this improvement is evidenced by a nearly 20% reduction in SAIFI, a 12% decrease in the SAIDI, and a 15% decrease in EENS values. Similarly, in the 33/11KV Udipur distribution system, the reliability gains are marked by a reduction of nearly 48% in SAIFI, 28% in SAIDI, and 29% in EENS values. Artificial intelligence (AI) is a burgeoning field witnessing considerable innovation and research across diverse scientific domains. Various sectors are leveraging AI methodologies to augment the performance and reliability of systems. Leveraging ANN techniques offers a novel approach to DG placement selection, mitigating human errors associated with trial-and-error methods and reducing computational complexities and time. The overall system's performance and effectiveness are evaluated through simulation using ETAP 19.0.1 software and results underscore that strategic DG placement substantially bolsters distribution system reliability.

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LIST OF ABBREVIATIONS

SYMBOLS	DEFINITION
ANN	Artificial Neural Network
ASAI	Average Service Availability Index
ASUI	Average Service Unavailability Index
CAIDI	Customer Average Interruption Duration Index
DS	Distribution system
DSS	Distribution Substation
EENS	Expected Energy not Supplied
ETAP	Electrical Transient Analyzer Program
HV	High Voltage
IEC	International Electro-technical Commission
LOL	Line overload
LV	Low Voltage
MP	Main Point
MTBF	Mean Time Between Failure
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
MVA	Megavolt Ampere
MWh	Megawatt Hour
RBTS	Roy Billinton Test System
SAIFI	System Average Interruption Frequency Index
SAIDI	System Average Interruption Duration Index
TTR	Times to Failure

CHAPTER ONE: INTRODUCTION

1.1 Background

The Reliability evaluation of a distribution system primarily focuses on how well it performs at the customer's end, where electricity demand is met. Key indicators used for predicting this reliability include the average failure rate at load points, the typical duration of outages experienced by customers, and the yearly cumulative outage time, or unavailability [1]. These indices are crucial for understanding reliability from both the customer's perspective and the utility's viewpoint. However, they don't offer a comprehensive overview of system performance. To achieve a more holistic understanding, additional indices can be derived from these basic indicators, considering the number of customers or loads connected at each load point in the system. Many of these additional indices are weighted averages of the fundamental load point indices. Among the most prevalent system-level indices are SAIFI, SAIDI, CAIDI, ASAI, ASUI, ENS, and AENS. Utilities often calculate these indices based on historical interruption data, offering valuable insights into past system performance [1]. Distributed Generation (DG) refers to electric-power generating units installed in close proximity to load centers. By avoiding transmission lines, the placement of distributed generation (DG) units strategically brings power generation closer to regions of demand. In contrast, a centralized model governs how a traditional electric supply system function, consisting of generation, transmission, and a distribution system. However, this conventional power system exhibits poor reliability owing to its complex configuration. A fault occurring at a single location within the system can trigger the entire feeder to trip, resulting in disruption to all consumers connected to that feeder [2].

An Artificial Neural Network (ANN) is an advanced machine learning technique inspired by the human capacity for imitation or learning through observation and replication [3]. Among the many types of artificial neural network (ANN) methodologies, the backpropagation (BP) learning algorithm has emerged as highly favored in engineering applications. This type of network typically comprises three layers: an input layer, a hidden layer, and an output layer. To effectively train and evaluate neural networks, datasets containing input patterns and corresponding targets are essential. When developing an ANN model, the available dataset is typically split into two subsets. The majority portion (around 70-80% of the data) is used for training the network, while the remainder is reserved to assess the network's ability to generalize beyond the training data[3]. Understanding different aspects of reliability is crucial when assessing the availability of power supply within a distribution system. One key reliability measure of significance is the failure rate of the distribution system. This index provides fundamental insight into the system's reliability and its ability to consistently deliver electricity without interruptions or breakdowns [4].

The training function of the feed-forward backpropagation network utilizes the Bayesian Regularization algorithm to update weight and bias values. This methodology is particularly suitable for training Neural Networks (NN), employing the mean squared error (MSE) as a performance metric. The backpropagation learning rule, integral to this process, is a continuous stochastic optimization technique aimed at minimizing the MSE between the actual and desired output[5]

The Levenberg-Marquardt algorithm (LMA), is adopted for training the network. This algorithm takes less time as training process automatically stops when generalizations stop improving as indicated by increase in Mean Square Error of validation samples. To maximize this improvement, placing DG units far from feeder rather than placing it close to load center[6].

The Udipur Substation, situated in Lamjung district of Nepal, is connected to a distribution network comprising four radial feeders: the Besisahar feeder, Bhoteodar feeder, Okhari feeder, and Nayagaun feeder. These feeders serve a total of 36,454 customers of various types. The combined radial length of these feeders extends to 129.5 kilometers, with an additional 112 kilometers comprising the lateral lengths. The radial sections utilize Rabbit conductors with a 50 mm^2 cross-sectional area, while the lateral sections use Weasel conductors with a 30 mm^2 cross-sectional area. Data on feeder tripping frequency and outage duration were collected over the year from 2079-07-01 to 2080-06-30. This data was used to calculate failure rates and Mean Time to Repair (MTTR) for each of the four feeders, and these data were subsequently integrated into the ETAP 19.0.1 software for a reliability assessment. The average load handled by the Udipur Substation is 3.412 MW, with the Besisahar feeder bearing the highest load among the four feeders.

1.2 Problem Statement

In the study area, a significant challenge arises from the unreliable supply of power to end-users, primarily stemming from distribution system failures. These failures occur due to aging of distribution system equipment's and various faults along distribution feeder lines, leading to interruptions in power delivery. Power interruptions not only affect customers but also critical infrastructures such as industries and businesses. Additionally, they contribute to equipment damage and maintenance challenges, ultimately impeding economic growth. Hence, it's imperative to promptly identify the root cause of this issue and explore potential solutions. Issues faced by the current power distribution system and the increasing demand for electricity. This involves penetration of distributed generation optimally to improve the reliability of distribution system.

1.3 Objective

1.3.1 General Objective

The major objective of this thesis is to enhance reliability through an examination of the reliability issues within the feeders of Udipur substation by locating DG optimally in the distribution network.

1.3.2 Specific Objective

- To calculate the reliability indices of the existing network without DG;
- To identify optimal location of DG using Hit and Trial Method based on the minimum values of SAIFI, SAIDI and EENS and
- To identify optimal location of DG using ANN and validate the results in ETAP simulation and compare the result with distribution systems reliability indices SAIFI, SAIDI and EENS without DG.

1.4 Significance of the Study

The main importance of this thesis is to improve reliability in a given distribution system. After the placement of DG optimally in a distribution network, reliability indices will be improved. Generally, the expected importance of this study is:

- To assess the average duration and frequency of power interruption per year in the system.
- Increase reliability of the system by reducing the interruption.
- Enhance the power supply for the society.
- Reduce power interruption influence on the customer.
- To show the feasibility of optimal DG placement on reliability improvement.

1.5 Scope of the study

This research studies the distribution system's present power system reliability issues, its tripping frequency, Outage duration and the reliability enhancement from including distributed generators in the present Lamjung Distribution Network and RBTS Bus-2 distribution network. The test and real system simulate using ETAP software and optimal location obtained from ANN training on MATLAB R2021a training toolbox based on the minimum values of SAIFI, SAIDI and EENS.

1.6 Assumptions and Limitations

- The study is limited to 11kV radial rural distribution system.
- Only forced outage have been taken into consideration for average failure rate and mean time to repair computation.
- The aging factor of equipment’s such as transformers, conductors, breakers, fuses etc. have not been taken into account.
- The magnitude of voltage has only been considered.
- Failure rate and repair rates for transformers, breakers and fuses have been taken as a default value in ETAP software taking into account only active failure rates.

CHAPTER TWO: LITERATURE REVIEW

2.1 Power System Reliability

The goal of the electric power system is to continuously supply energy to load points or consumers while respecting environmental and financial constraints. Transmission lines transport the electricity generated at power plants, and distribution lines deliver it to consumer terminals. The complete system is referred to as the power system. Its effectiveness in fulfilling its intended purpose is termed as its reliability. In order to improve consumer supply reliability, more money should be invested in the system either in the planning phase, the operational phase, or both. Although overinvesting in the system could increase supply reliability, it might also violate budgetary restrictions. Conversely, inadequate investment may result in poor reliability for customers. Therefore, when making managerial decisions in both the system's planning and operational stages, it is crucial to strike a balance between financial restrictions and system reliability as well as adhere to environmental issues in modern contexts[7].

A power system can be segmented into three subsystems based on their functions: generation, transmission, and distribution,[7], [8], [9], [10] as depicted in Fig. 2.1. The analysis of generation reliability is categorized under hierarchical level 1 (HL-1), wherein the overall power generation is modeled and compared with the system load model across a planned horizon to evaluate system risk using various load and energy-based indices[8], [9]. At hierarchical level 2 (HL-2), transmission constraints are also factored into the generation model, constituting what is known as bulk system reliability assessment[10], [11]. Presumptive dependability evaluation is typically not carried out at hierarchical level 3 (HL-3), which includes all three functional zones. Distribution system (DS) dependability evaluations are carried out independently for investment and operational planning. Power for several distribution systems comes from the bulk system and is owned by different entities.

Historically, more emphasis has been placed on the evaluation of generation and bulk system reliability compared to distribution system (DS) reliability. This is attributed to the potential for widespread catastrophic consequences on society and the environment due to inadequacies in generation and transmission, whereas the impact of DS inadequacies tends to be localized. However, research indicates that around 80% of unreliability events stem from Distribution system components[7], [12], [13]. Utility planners and regulatory agencies have been forced by this revelation to give increasing DS reliability top priority in order to efficiently serve customers' requirements.

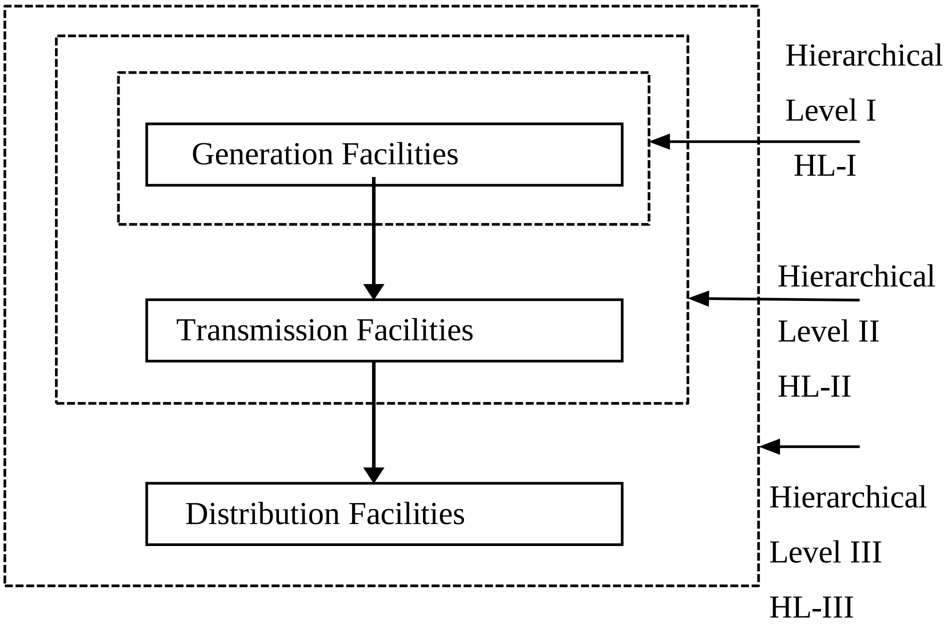

Fig. 2.1: Hierarchical levels in reliability assessment [7].

2.2 Power Distribution System

A distribution system receives electricity from the bulk system via one or more transmission lines and distributes it to various categories of electricity consumers. Fig. 2.2 illustrates a typical radial DS that supplies power to rural customers, while Fig. 2.3 depicts a DS with a meshed network typically serving urban customers[14]. These DSs are collectively referred to as utility DSs and they serve a wide variety and a large number of customers. Typically, urban distribution feeders are relatively short, whereas rural distribution feeders are long and widely dispersed. Urban distribution feeders frequently include the capacity to shift loads from nearby feeders in the event that a particular feeder needs maintenance or an emergency arises. A DS's choice in a given location is impacted by a number of technical, financial, environmental, and geographic considerations in addition to the kinds of loads that need to be delivered and the types of consumers.

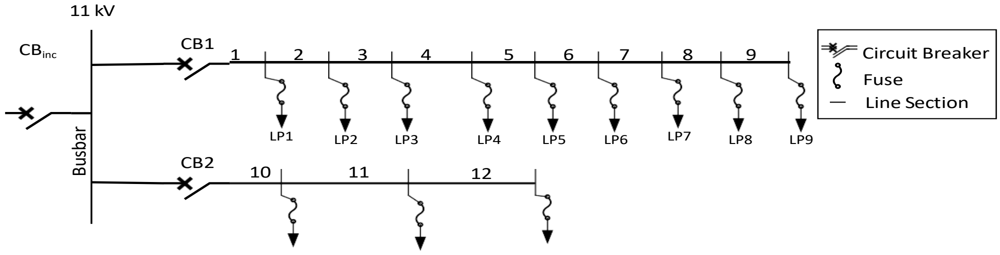

Fig. 2.2: A typical rural distribution system.

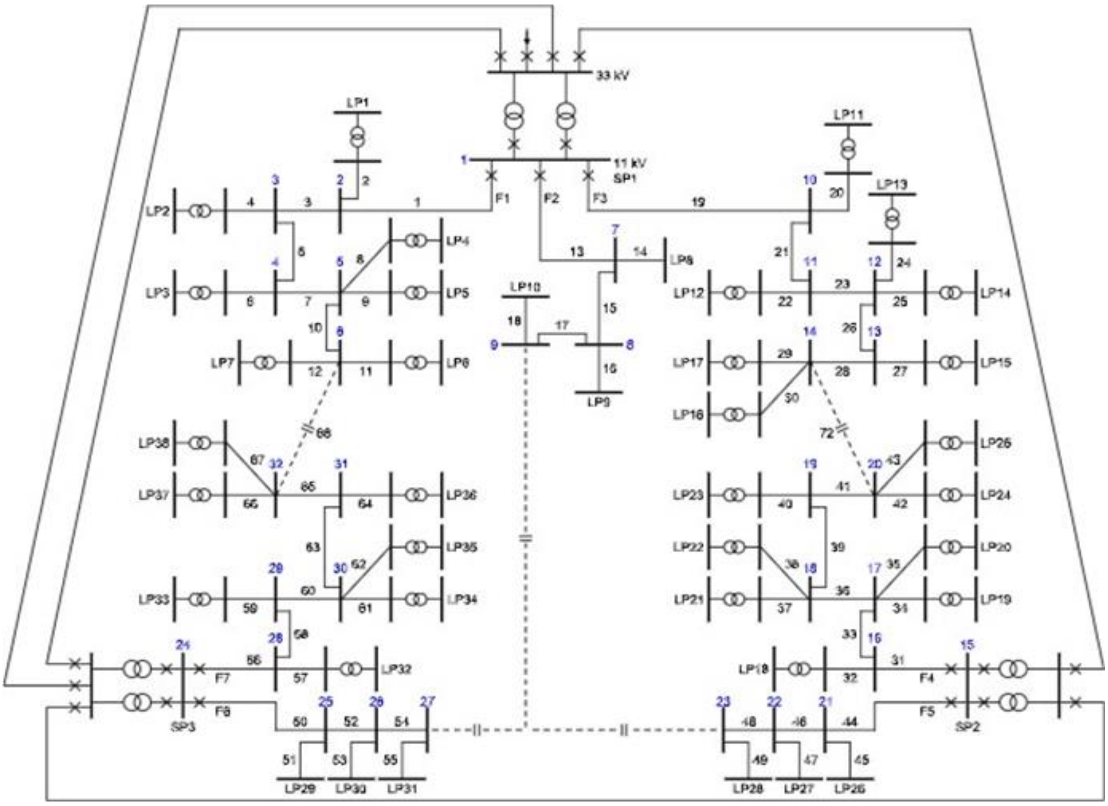

Fig. 2.3: A typical urban distribution system[15].

2.3 Power Interruption Causes and Reliability Performance Influencing Factors

The majority of power outages experienced by customers, approximately 90%, are due to failures within the distribution system. It is essential to evaluate the impact of these outages on customer outage costs and overall system reliability. Given that distribution system equipment failures are the primary cause of service interruptions, the significance of distribution system (DS) reliability in the provision of electric power to specific load sites is underscored. The breakdown of outages by functional area is as follows: 85% of customer service hours lost are due to distribution system issues (such as poles, wires, cables, and switchgear), 9% are attributable to substation failures, 4% to transmission faults, and less than 2% to generation problems[16], [17]. This is mainly because most electric power distribution systems are radial in design, as shown in Fig. 2.2.

Power outages and breakdowns in distribution networks are caused by a variety of power system issues. Traditional power systems, in contrast to the smart grid, are vulnerable to several failure sources, leading to an unstable power supply. Consequently, the system's reliability is determined by the aggregate effect of various power failure sources. Critical factors include exposure to natural elements (such as whether conductors are overhead or underground), sectionalizing capability, redundancy, the age of conductors, and the number of customers connected to each feeder[18]. As a result, different locations and systems have different dependability performance levels for the distribution system. Numerous factors that affect predicted dependability performance at particular places or across large systems are the cause of this unpredictability. Among the primary physical factors influencing reliability, some are outlined below:

- Geographic features of the service area, such as dense forests or mountainous terrain.
- System components' exposure to natural elements; for instance, transmission and distribution system elements may be vulnerable due to their exposure to the surrounding environment.
- Weather conditions, including extreme weather events like high winds, heavy rain, and lightning.
- Impact of vegetation, such as trees falling or branches encroaching on power lines.
- Influence of animal activity, such as birds and pests causing ground faults.

Additional factors to consider are:

- System voltage.
- Length and design of feeders.
- Customers located farthest from the supply point generally experience the highest frequency of outages and the longest periods of downtime.
- Sectionalizing capability.
- Redundancy.

- A system with multiple components, where the operation of any single component maintains system functionality, is known as a redundant system.
- Type and age of conductors.
- Number of customers served by each feeder.

For a country to advance, it must guarantee a reasonably priced, reliable electricity source. Electric power companies must therefore make a major effort to improve the network in order to satisfy customer reliability requirements and regulatory standards at the lowest possible cost[19].

2.4 Strategies for Enhancing Distribution System Reliability

In this context, the primary strategy for improvement revolves around minimizing the occurrence and duration of power interruptions. However, devising methods to reduce the number of power outages poses a significant challenge, as some of the potential solutions may entail high costs. Furthermore, determining where to initiate improvement efforts for the distribution system is a key issue. Nevertheless, at utilities where reliability indices are systematically gathered, engineers and operational staff can readily identify reasonable starting points for improvement.

Improving system reliability requires decreasing both the frequency and duration of faults. The main strategy to enhance reliability and power quality for customers focuses on promptly addressing faults and mitigating their effects on customers when they do occur. A range of techniques, including both electrical and non-electrical methods, have been suggested to improve system reliability[20].

Non-electrical methods for improvement include:

- Trimming trees along the right-of-way for overhead lines.
- Installing animal guards on distribution circuits.
- Using lightning arresters.
- Allocating crews and taking human factors into account.

Electrical methods for improvement include:

- Adding extra protective devices such as re-closers, fuses, and switching devices.
- Reconfiguring the system, reconnecting feeders, and sectionalizing.

- Installing Distributed Generation at the distribution center towards the end of the feeder.
- Enhancing preventative maintenance and inspection procedures for distribution system components, including poles, fuses, transformers, and lines.

2.5 Analysis and Evaluation of Power Distribution System Reliability

The dependability of power distribution encompasses both system security and adequacy. System adequacy, which examines static conditions, ensures that there is sufficient generation, transmission, and distribution capacity to meet customer demand. Conversely, system security focuses on the system's response to disruptions, reflecting the dynamic conditions of the power system. Given that distribution system components are typically not heavily loaded, system security holds greater importance, making system adequacy less critical[7].

Reliability analysis becomes crucial in assessing, predicting, and comparing reliability indices to support various improvement initiatives. It facilitates the evaluation of past performance and the prediction of future reliability, identifying problematic components that could affect reliability. Additionally, it ensures appropriate reliability levels within the system, provides essential data for regulatory bodies to establish benchmarks, and predicts the impact of system expansion or the addition of new components[21].

Several methods have been developed by researchers to assess the reliability of distribution systems. Different techniques and algorithms are used by each method to evaluate and improve the dependability of electricity distribution to residential, commercial, and industrial consumers. Customers and utilities alike have serious concerns about the reliability of distribution systems, and methods for evaluating reliability are essential to the design, construction, and operation of these systems. Low reliability can result in increased operation and maintenance expenses. These can be minimized by proper planning, ongoing behavior monitoring of the system, and appropriate control actions[22].

Reliability analysis is an essential instrument for locating vulnerable parts in electrical power systems that need special attention in order to improve overall performance and raise system availability. Its main objective is to measure, forecast, and contrast reliability indices in order to facilitate different programs meant to increase reliability. Evaluation of reliability is important in a number of ways:

- It enables the assessment of past performance and the prediction of future performance of the distribution system.
- It aids in identifying components within the system that pose reliability challenges and can impact overall system reliability.
- It ensures that appropriate levels of system reliability are maintained and provides valuable information for regulatory bodies to establish suitable benchmarks.
- It makes it easier to forecast the reliability of the system after it has expanded and aids in estimating the effects of adding additional system components.

2.5.1 Bathtub-Shaped Hazard Rate Curve

Reliability, defined as the likelihood of a component or system performing its intended function without failure over a specified time under specific conditions, is a crucial aspect in engineering. The failure rate, also known as the hazard rate, is a key metric in reliability analysis as it indicates the probability of failure throughout the component's lifespan. Typically, the failure rate follows a bathtub curve, showcasing distinct phases: the burn-in period, useful life period, and wear-out period.

The burn-in period marks the initial phase where the hazard rate decreases. Failures during this phase can be attributed to various factors such as poor-quality control, inadequate manufacturing methods, human error, substandard materials, and insufficient debugging processes. This phase is also referred to as the "infant mortality region," "break-in region," or "debugging region."

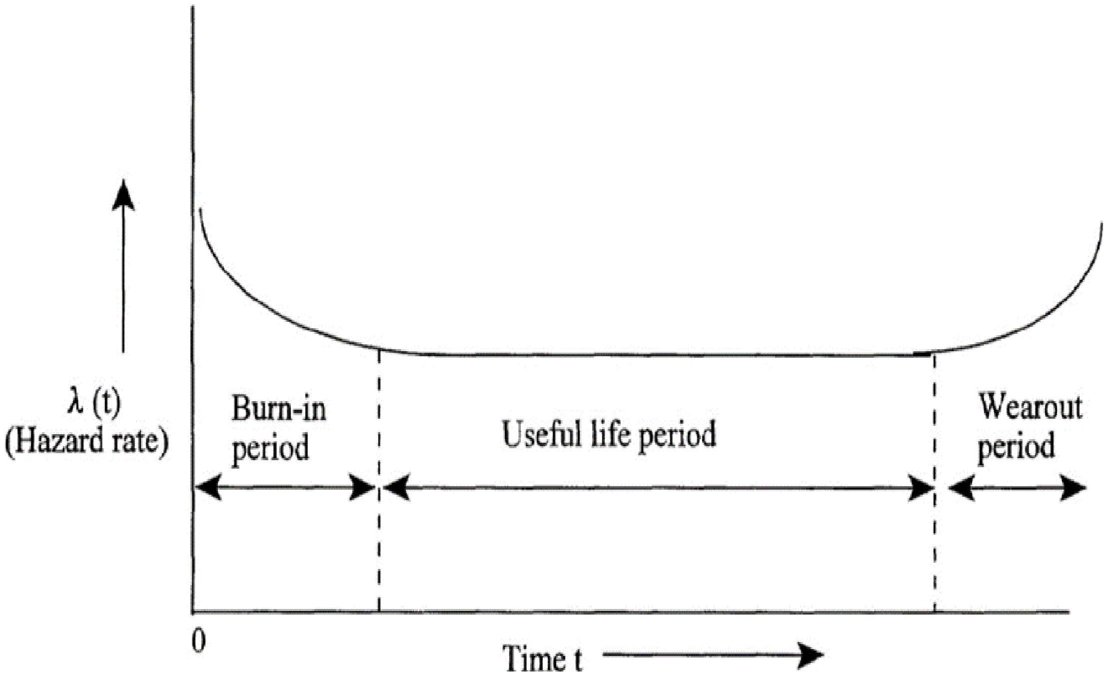

Fig. 2.4: Bathtub Hazard Rate Curve[23].

The hazard rate is constant during the useful life period, and failures can be attributed to a variety of things, such as imperceptible flaws, inadequate safety precautions, abuse, unexpectedly high random stress, human error, natural failures, and explicable reasons. This phase includes the time frame in which parts should operate reliably under typical operational circumstances[23].

As the system progresses into the wear-out period, the hazard rate starts to increase. Failures during this phase, known as the "wear-out region," stem from various causes such as aging-related wear, corrosion, and creep. Additionally, factors such as a short designed-in life span, inadequate maintenance practices, friction-induced wear, and incorrect overhaul procedures contribute to failures during this stage. This phase signifies the end of the component's expected lifespan, where deterioration becomes more pronounced, leading to an elevated risk of failure.

2.5.2 Momentary and Sustained Interruption

Sustained interruptions are prolonged disruptions that exceed 5 minutes, while interruptions shorter than 5 minutes are considered momentary[24]. Typically, regulatory authorities receive reports solely on sustained interruptions, as they are considered more significant in terms of impact and duration.

Distribution circuits with permanent faults frequently experience prolonged disruptions that impact at least some consumers. In order to restore regular service, these persistent disruptions may result in extended periods of outage that call for intervention and restoration.

Sustained interruptions can be divided into Planned and Unplanned Interruptions. Planned interruptions are scheduled at times that are less disruptive for customers, with advance notice provided to those affected. In contrast, unplanned interruptions happen unexpectedly, without prior notice. These interruptions can result from fault clearing, accidental operation of protection systems, or human error that triggers the opening of switching devices. Planned interruptions are generally conducted for activities such as construction, preventive maintenance, or repair work. They are timed strategically to reduce inconvenience to customers while allowing essential operations to be carried out[25].

Planned Interruption: This refers to disruption during the operation and maintenance of the system, which are communicated to customers in advance. It encompasses activities such as operational adjustments (such as voluntarily interrupting outgoing lines for maintenance purposes), circuit breaker repair and replacement, load transfers, erection of new transformers, and similar tasks.

Unplanned Interruption: These interruptions occur as a result of various faults, including permanent and transient Earth faults, short circuits and overloading of distribution line.

Earth Fault: An Earth fault occurs when there is any deliberate or accidental connection between an electric conductor and any grounded conducting material. In essence, electricity seeks a path to the ground. In the event of a ground fault, electricity finds a route to the earth, but through a pathway not intended for it, such as passing through a person's body.

This fault typically occurs due to insulation breakdown between a live conductor and an exposed conducting element. It presents a significant risk to people in addition to having the ability to harm electrical equipment. People could unintentionally come into contact with an exposed conductive part in these circumstances. These parts are often not live, but because of the fault, they could potentially be dangerously close to the ground.

Short circuits: These are common cause of power outages, and they are indicated by an electric current in an electrical circuit that veers off course. An excessive electric current caused by this aberration may result in explosions, fires, and damage to circuits. Worldwide, one of the main causes of electrical fires is short circuits. They may appear as a result of deteriorating wiring insulation or unintentional entry of external conducting materials, like water, into the circuit. It is essential to protect electrical switchboards, wires, and circuits against water exposure. Additionally, a buildup of dust can be dangerous for electrical systems, possibly resulting in short circuits and subsequent power outages.

Distribution Line Overload: These occurs as a result of rising electricity use, which puts stress on the current power infrastructure. One of the main causes of line voltage variations is overloading. Problems with power distribution and generation, for example, exacerbate line voltage issues. Voltage fluctuations may also result from the usage of power regulating devices that are inappropriate or poorly built. Voltage irregularities may also arise from poorly secured or oxidized connections at the termination point of the electric service subscriber, as well as by comparable circumstances along the distribution power lines. Poor infrastructure is the cause of many voltage fluctuation incidents[25].

2.5.3 Terminologies of Reliability

Availability(A): Availability refers to the duration during which a component remains operational at any given time. It pertains to the period in which the system functions fully and effectively to fulfill its designated purpose[26].

$$\text{AVAILABILITY} = \frac{\text{MTBF}}{\text{MTBF}+\text{MTTR}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2.1)}$$

Unavailability(U): Unavailability denotes the timeframe when a component is not functioning.

$$\text{UNAVAILABILITY} = \frac{\lambda}{\lambda+\mu} \quad \dots\dots (2.2)$$

Failure Rate(λ): The frequency with which component fails, expressed in failures per unit of time[26].

$$\lambda = \frac{\text{The frequency of component failures in a given period}}{\text{Agreegate operational duration of component}} \quad \dots\dots (2.3)$$

Mean Time to Repair (MTTR): MTTR is the average time it takes to fix a faulty component and return it to normal operation. In other words, it represents the typical duration a component is out of service due to a fault before it is restored to working condition [26].

$$\text{MTTR} = \frac{\text{Total Duration of Outages}}{\text{Frequency of Outage}} \quad \dots\dots (2.4)$$

Mean Time Between Failure (MTBF): MTBF is the average amount of time a component, assembly, or network operates without failure, assuming the failure rate is constant. It indicates the total time the element is functional before experiencing a failure [26].

$$\text{MTBF} = \frac{\text{Total System Operating Time}}{\text{Frequency of Outage}} \quad \dots\dots (2.5)$$

2.5.4 Reliability Indices

2.5.4.1 Load Point Reliability Indices

2.5.4.1.1 Average Failure Rate (λ): Interruptions/ year.

The mean rate of failures indicates the expected number of failures a load point will encounter within a defined time frame[1], [2], [5], [27].

$$\lambda = \sum_{i=1}^{n} \lambda_i \quad \dots\dots (2.6)$$

2.5.4.1.2 Annual Outage Duration(U): Hours/year[1], [5].

The mean duration of outages represents the typical length of time a load point encounters a power interruption.

$$U = \sum_{i=1}^{n} r_i * \lambda_i \quad \dots\dots (2.7)$$

2.5.4.1.3 Average Annual Outage Duration(r): Hours/failure

The average yearly outage duration, usually measured in annual hours, signifies the cumulative time during which a load point encounters power interruptions over a year, averaged across an extended period. This metric aids in evaluating the reliability and quality of power supply services[1], [5].

$$r = \frac{\sum_{i=1}^{n} r_i * \lambda_i}{\sum_{i=1}^{n} \lambda_i} = \frac{U}{\lambda} \quad \text{.......... (2.8)}$$

2.5.4.2 System Reliability Indices

2.5.4.2.1 System Average Interruption Frequency Index (SAIFI): Failure/ year. Customer

SAIFI represents the mean occurrence rate of power interruptions experienced by each utility customer within a specified analysis period. It is determined by dividing the total number of customer outages by the total number of customers in the network. This measure is typically assessed annually[1], [2], [3], [5].

$$SAIFI = \frac{\sum_{i=1}^{n} \lambda_i * N_i}{\sum_{i=1}^{n} N_i} \quad \text{.......... (2.9)}$$

λ_i = Average failure rate

N_i = Number of customers at load point i.

It helps utility companies to understand the frequency of outages that their customers face, indicating the reliability of the power supply.

2.5.4.2.2 System Average Interruption Duration Index (SAIDI): Hours/ year. Customer

SAIDI reflects the mean duration of all interruptions encountered by each utility customer throughout the analysis period. It is calculated by dividing the total sum of interruption durations for all customers by the total number of customers served by the network.[1], [2], [3], [5] .

$$SAIDI = \frac{\sum_{i=1}^{n} U_i * N_i}{\sum_{i=1}^{n} N_i} \quad \text{.......... (2.10)}$$

U_i = Annual Outage Duration.

SAIDI indicates the total amount of time the average customer is without power during measurement period, giving insights into the utility’s ability to restore service after interruptions.

2.5.4.2.3 Customer Average Interruption Duration Index (CAIDI): Hours/ Failure

It represents the mean time required to restore service to the average customer for each sustained interruption. It provides the average duration of a customer interruption and is calculated by dividing the total sum of all customer interruption durations by the total number of customer interruptions[5].

$$\text{CAIDI} = \frac{\Sigma(U_i * N_i)}{\Sigma(\lambda_i * N_i)} = \frac{\text{SAIDI}}{\text{SAIFI}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2.11)$$

Utilities use CAIDI, along with SAIFI and SAIDI, to assess the reliability of power distribution networks, set performance benchmarks, and guide infrastructure investments and maintenance strategies. By analyzing these indices, utilities can identify areas needing improvement, optimize response strategies, and enhance overall service reliability.

2.5.4.2.4 The Average Service Availability Index (ASAI)

ASAI, quantifies the proportion of time that a customer receives power during a predefined time interval. ASAI is calculated as the ratio of the total number of customer hours that service was available during a specified time period to the total customer hours demanded. It is normally expressed in percentage[5], [6], [28].

$$\text{ASAI} = \frac{\text{Total duration of service available to customers}}{\text{Total duration of service requested by customers}} * 100\%$$

$$\text{ASAI} = \frac{\sum_{i=1}^{n} N_i * 8760 - \sum_{i=1}^{n} U_i * N_i}{\sum_{i=1}^{n} N_i * 8760}$$

$$\text{ASAI} = \frac{8760 - \text{SAIDI}}{8760} * 100\% \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2.12)$$

Higher ASAI indicates highly reliable distribution system with minimal interruptions whereas lower ASAI indicates frequent or prolonged outages, indicating a less reliable system.

2.5.4.2.5 The Average Service Unavailability Index (ASUI)

This index represents the proportion of total customer hours during a year when service was not available, relative to the total customer hours demanded [5], [6], [28].

$$ASUI = (100 - ASAI)\ \% \quad (2.13)$$

2.5.4.2.6 Average Energy Not Supplied (AENS)

The mean energy shortfall experienced by an average customer due to power supply interruption [1], [28].

$$AENS = \frac{\text{Total amount of energy not supplied}}{\text{Total number of customers served}}$$

$$AENS = \frac{\sum_{i=1}^{n} U_i * L_i}{\sum_{i=1}^{n} N_i} \quad (2.14)$$

2.5.4.3 Cost Worth Reliability Indices

2.5.4.3.1 Expected Energy Not Supplied (EENS): MWhr /year

EENS defines the average energy that customers do not receive within the predefined timeframe [1], [2], [5].

$$EENS = \sum_{i=1}^{n} U_i * L_i \quad (2.15)$$

L_i = Average load connected to load point i.

U_i = Annual Outage duration at load point i.

EENS is a significant index for evaluating the reliability of electric power systems, providing insights into the energy not delivered to customers due to outages. By analyzing EENS, utilities can make informed decisions to enhance system reliability, reduce economic losses, and improve service quality.

2.6 Distributed Generation

2.6.1 Introduction

In conventional power systems, electricity generation relied on centralized generators, with transmission lines distributing power to local distribution networks. This setup posed numerous challenges, including high transmission costs, environmental concerns, and issues with voltage and frequency stability. However, with the escalating global population and growing energy demands, power consumption has surged[29].

In response, many nations are turning to Distributed Generation (DG) to supplement their energy needs. DG involves smaller-scale generation units located closer to end-users, offering several advantages over traditional systems. By decentralizing power production, DG helps mitigate transmission expenses and reduces environmental impact. Furthermore, DG systems enhance grid resilience by providing localized generation, thus bolstering voltage and frequency stability. This shift towards distributed generation represents a proactive approach to meeting escalating energy demands while addressing longstanding challenges associated with centralized power systems. Distributed Generation (DG) is emerging as a novel approach in power systems to meet the growing energy demand, reduce peak loads, and serve as a standby power source. “Distributed generation is considered as an electrical source connected to the power system, in a point very close to/or at consumer´s site, which is small enough compared with the centralized power plants.”

2.6.2 Classification of DG

Distributed Generators (DGs) are classified into four main categories according to their performance in supplying active and reactive power. These classifications are as follows[29]:

- Type 1: DGs exclusively possess the capability to supply real power (P).
- Type 2: DGs solely have the capacity to supply reactive power (Q).
- Type 3: DGs are equipped to supply both real power (P) and reactive power (Q).
- Type 4: DGs capable of supplying real power (P) while consuming reactive power (Q).

Type 1 devices, such as photovoltaic panels, microturbines, and fuel cells, are seamlessly integrated into the main grid through converters and inverters, enabling them to exclusively supply real power (P).

Type 2 synchronous compensators, which include gas turbines, are primarily capable of injecting reactive power (Q).

Type 3 encompasses cogeneration systems, gas turbines, and other distributed generation units employing synchronous machines, offering the ability to inject both real power (P) and reactive power (Q).

Type 4 devices, like induction generators commonly utilized in wind farms, are characterized by their capability to supply real power (P) while consuming reactive power (Q).

2.6.3 Benefits of DG

Connecting Distributed Generation (DG) offers numerous benefits[29]:

- Improves the reliability of power supply and reduces losses in transmission and distribution systems.
- Improves voltage profile, elevates power quality, and reinforces voltage stability, enabling the system to endure higher load conditions.
- Certain DG technologies, such as combined heat and power (CHP) systems and microturbines, boast low pollution levels and exceptional overall efficiency. Renewable energy-based DG, like photovoltaic (PV) and wind turbines, significantly contribute to reducing greenhouse gas emissions.
- Augments overall energy efficiency and bolsters system security.

2.6.4 Drawbacks of DG

Integrating Distributed Generation (DG) into existing distribution systems presents both advantages and challenges[29].

- Power converters are essential for DG-grid connection, but they can introduce harmonics into the system.
- Without proper coordination with the utility supply, DG connection may lead to overvoltage, voltage fluctuations, and imbalance in the system.
- Depending on factors like network configuration, penetration level, and DG technology, DG injection may increase distribution system losses.
- Integration of DG alters short-circuit levels, necessitating adjustments to relay settings. In case of DG disconnection, relays must revert to their original settings.

2.7 Artificial Neural Network

2.7.1 Introduction

An Artificial Neural Network (ANN) is a computational model that mimics the information processing mechanism of biological nervous systems, such as the human brain. Its characteristic feature lies in its specialized structure designed for information processing. Neural networks have a remarkable capability to interpret meaning from complex or imprecise data, making them useful for extracting patterns and detecting trends that are too intricate for humans or other computational methods to identify. Once trained, a neural network can be regarded as an "expert" in the specific category of information it has been trained to analyze. This expertise allows the network to make predictions in new situations and answer "what if" questions effectively[30]. ANN is a mathematical or computational model, an information processing paradigm inspired by the way biological nervous systems, such as the brain, process information. ANNs consist of interconnected artificial neurons programmed to mimic the properties of biological neurons. These artificial neurons work together to solve specific problems. ANNs are designed to address artificial intelligence problems without replicating the real biological systems. They are used in applications such as speech recognition, image analysis, and adaptive control. These applications are accomplished through a learning process, similar to learning in biological systems, which involves adjusting the connections between neurons, known as synaptic connections[31].

2.7.2 Characteristics of ANN

2.7.2.1 Learning

Neural networks (NNs) pick up knowledge from examples, their architectures can be trained on well-known examples of a problem before being evaluated on new examples to see how well they can draw conclusions. This enables them to recognize new objects not encountered during training. Artificial neural networks (ANNs) have the capability to adapt their behavior based on environmental feedback. When presented with input data, they adjust themselves to generate consistent responses, potentially with desired outputs. A diverse range of training algorithms has been explored in subsequent units to facilitate this learning process[32].

2.7.2.2 Parallel Operation

Neural networks (NNs) have the capacity to process information simultaneously, operating at rapid speeds, and in a distributed fashion.

2.7.2.3 Mapping

Neural networks (NNs) demonstrate mapping capabilities, meaning they can establish relationships between input patterns and their corresponding output patterns.

2.7.2.4 Generalization

Neural networks (NNs) possess the capacity for generalization, allowing them to forecast new outcomes by extrapolating from past patterns. Following training, a network's reaction can remain quite consistent even with slight fluctuations in its input. In real-world scenarios, the capability to recognize patterns amid noise and distortion is vital for successful pattern recognition. It's crucial to highlight that the automatic generalization of artificial neural networks (ANNs) arises from their intrinsic structure rather than depending on human intelligence integrated into ad hoc computer programs.

2.7.2.5 Robust

Neural networks (NNs) are robust and fault-tolerant systems. They have the capability to retrieve complete patterns even from incomplete, partial, or noisy inputs.

2.7.2.6 Abstraction

Some artificial neural networks (ANNs) can distill the core features of a provided set of inputs. They can derive characteristics from the provided data. For example, convolutional neural networks (CNNs) excel at deriving diverse features from images, including edges, shadows, and shapes. These networks undergo training to recognize feature patterns, enabling them to classify or cluster the input data accordingly.

2.7.2.7 Applicability

ANNs are not universally applicable solutions. They are notably unsuitable for tasks like payroll calculations. However, they excel in a wide range of pattern-recognition tasks where conventional computers struggle or fail altogether.

2.7.3 Applications of ANN

Neural networks are the favored choice for tasks that involve extensive data processing. Below are the potential uses of neural networks[33]:

- Categorization
- Forecasting
- Data Linking
- Data Abstraction
- Data Screening
- Optimization

2.7.4 The Biological Prototype

Artificial Neural Networks (ANNs) represent a supervised learning method in machine learning, utilizing labeled inputs. They emulate the biological neural networks of the human brain (Fig.1). The human brain orchestrates thought and behavior. Understanding the brain's structure, including neurons and their functions, provides insights into the complex networks formed by biological neurons. The brain consists of numerous neurons, or nerve cells, interconnected through synapses, creating intricate neural networks.

Synaptic function is crucial. Neurons transmit signals to each other through synapses, forming the basis of modern neuroscience. Human brains exhibit self-learning capabilities due to extensive parallel computing and distributed information processing within neural networks. Scientists aim to leverage computer-based programs to mimic this self-learning ability. Consequently, ANN structures are designed to mirror the human nervous system's parallel computing model.

ANN technology, also known as the parallel distributed processing (PDP) model or connectionist model, processes information similarly to the brain and nervous system. ANNs consist of numerous artificial neurons (or nodes) capable of parallel computing and distributed information processing, thanks to the high computational speed of modern computers. However, ANNs still fall short of replicating the full functionality of human brain cells due to the sheer number of neurons. The complete operations of brain cells cannot be entirely implemented in ANNs, and computation time remains a significant challenge, necessitating improvements in ANN algorithms.

The human brain's anatomical structure is layered, specifically comprising the six layers of the mature brain cortex, essential for higher-order cognition. Complex thinking operations rely on this layered structure, the number of neurons, and their connection styles. ANNs emulate the operations of biological neural networks through mathematical functions (activation functions) and parameters (weights and biases). Fig.2.5 illustrates a simple structural map of a biological neuron. As depicted in Fig. 2.5, a biological neuron can be segmented into the following parts:

Dendrite: This part receives electrochemical signals from preceding neurons, acting as the input to the neuron.

Axon Hillock: Situated between the cell body and the axons, it converts the electrochemical signals into a membrane potential.

Axon: As a component of a nerve fiber, it transmits the membrane potential, formed at the Axon Hillock, as an action potential.

Synapse: Its function is to convert the action potential into electrical and chemical signals, which are then conducted to the next neuron when the action potential reaches or exceeds a certain threshold.

Although a biological neuron is highly intricate, only these four main components are highlighted here because ANNs emulate these specific parts[34].

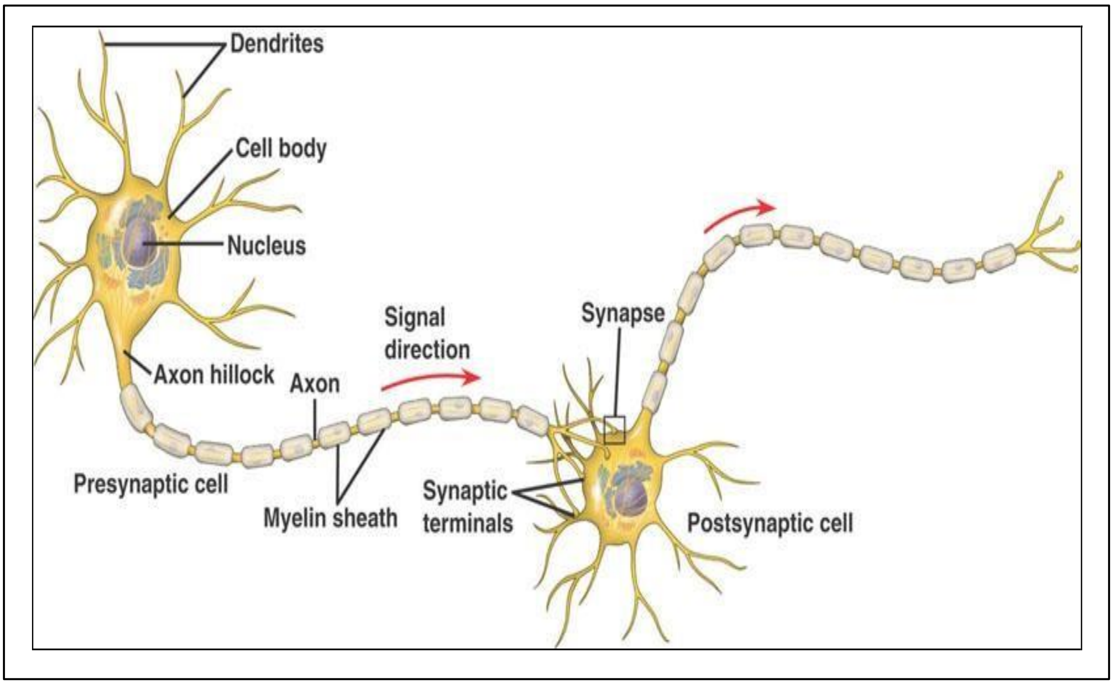

Fig. 2.5: A diagrammatic representation of a Biological Neuron[34].

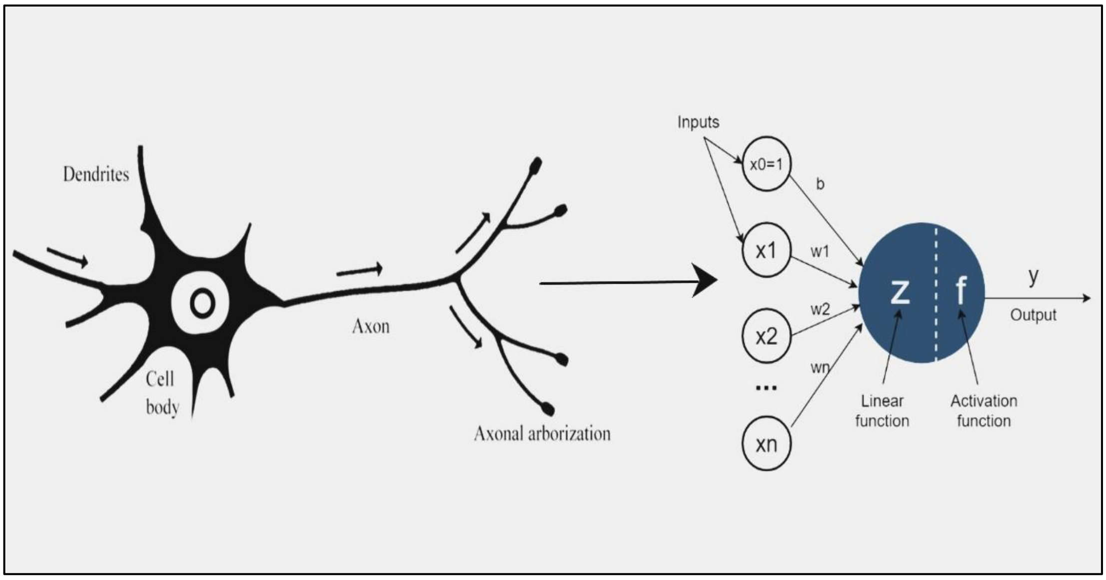

Fig. 2.6: A simple Neuron and ANN comparison diagram[35].

Table 2.1: Biological Neuron verses ANN

Human	**Artificial**
Neuron	Processing Element
Dendrites	Combining Function
Cell Body	Transfer Function
Axons	Element Output
Synapses	Weights

CHAPTER THREE: METHDOLOGY

3.1 Introduction

This chapter provides the overall methodology and approach for reliability evaluation of distribution systems and optimal placement of DG for reliability enhancement. For reliability analysis, various parameters such as interruption frequency, interruption durations, total number of customers served, feeder and section lengths, loads connected, conductors used, average loads etc., are required. This chapter presents the failure data related to tripping frequency, Outage duration, Number of Customers connected, Average load collected along with the fundamental electrical data of power system equipment.

3.2 Data Collection

Data was compiled from the Lamjung distribution center of Nepal Electricity Authority for 33/11KV Udipur distribution system and reference paper by S. Ahmad and A. U. Asar, "Reliability enhancement of electric distribution network using optimal placement of distributed generation," *Sustain.*, vol. 13, no. 20, 2021, doi: 10.3390/su132011407 for RBTS bus-2 distribution system. The data collected includes the quantity and ratings of transformers, Number of Customers for different types such as Residential, Commercial, Industrial and Governmental and Institutional customers, feeder length, interruption frequency, interruption durations, types of conductors used in radial and lateral sections of feeder, average load of one year from 2079-07-01 to 2080-06-30. Appendix A and Appendix B provides detail on the Average load, Number of Customers, Types of different customers for RBTS Bus-2 distribution system and 33/11KV Udipur distribution system respectively. Failure rates and MTTR values for four feeders for Udipur distribution system were calculated from the collected data for Tripping frequency and Outage duration.

3.3 Modelling of the system

ETAP can be a valuable asset for performing technical and reliability assessments on power systems. Nevertheless, a strong understanding of power systems and the specific analyses we plan to conduct is essential before using this software.

3.3.1 Modelling of the Test system

The RBTS Bus-2 Distribution system was simulated using ETAP 19.0.1. The types of customers at different load points along with number of customers, Reliability information such as Failure rate and Repair Time data for critical components such as Power Transformer, Distribution Transformers, Breakers, Busbars, cables were taken from the reference paper. All the buses were connected accordingly as shown in the reference paper. Following with that all the load of particular load end were modeled. The Cable lengths were also inserted as per reference paper. After all the available data were input into the model system, it was executed. Then Distributed Generation (DG) i.e., wind turbine generator, capacity 1 MW modelled as a Type-III DG source in generic mode within ETAP having failure rate of 0.03 failures per year and repair time of 50 hours with Circuit Breaker in series for protection was modelled. The single line diagram of RBTS Bus-2 distribution system is shown in Fig 3.2. This diagram consists of four numbers of sub feeders and all combined 22 load points, 14 Main points, 22 numbers of 2 MVA, 11/0.4KV distribution transformers, circuit breakers and cables. The system has a total of 1878 customers connected to it with an average load of 12.656 MVA as shown in Appendix A.

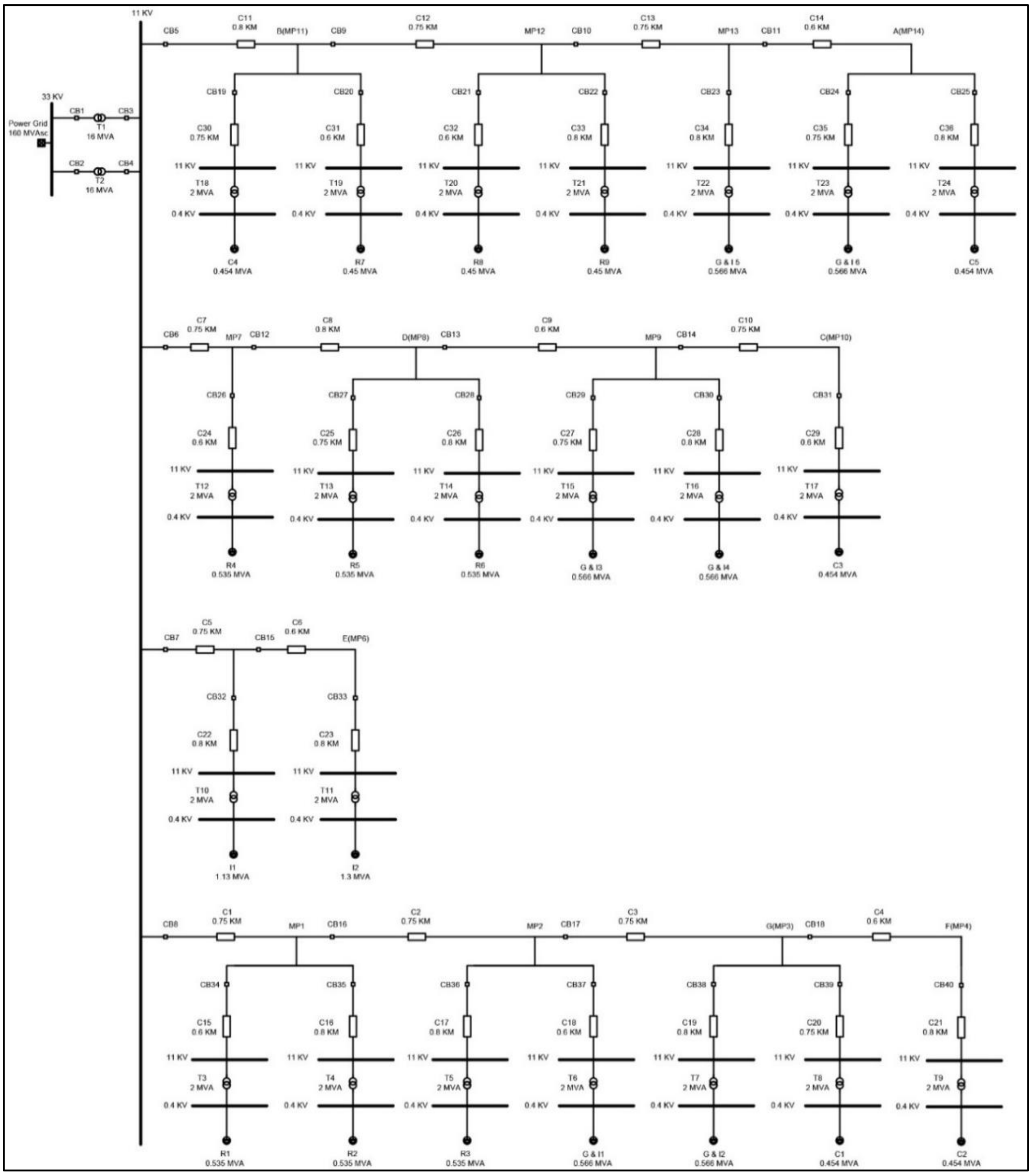

Fig. 3.1: Single line diagram of RBTS BUS-2 Distribution System

3.3.2 Modelling of the real system

The real system of 33/11KV Udipur distribution system containing four numbers of Outgoing feeders was modeled in the ETAP 19.0.1. The single line diagram of 33/11KV Udipur distribution system is as shown in Fig. 3.2. This diagram consists of four numbers of sub feeders and all combined have 57 numbers of load points, 36 numbers of Main points, 57 numbers of different ratings lumped transformers of 11/0.4KV distribution transformers, 2 numbers of 8 MVA, 33/11KV power transformers, circuit breakers and fuses. All the feeder lengths including radial and lateral sections, types of conductors used in the radial and lateral sections, number and type of customers connected to each load points, lumped KVA ratings of distribution transformers were taken as real data from NEA Lamjung Distribution Centre. Tripping frequency and Outage Duration of feeders were taken from the log sheet of substation of one year from 2079-07-01 to 2080-06-30 from which failure rates and MTTR for four feeders were calculated and inserted into ETAP reliability assessment section. Power Transformers, Circuit Breakers, Fuses, Distribution Transformers failure rate and repair rates are taken as per reference paper.

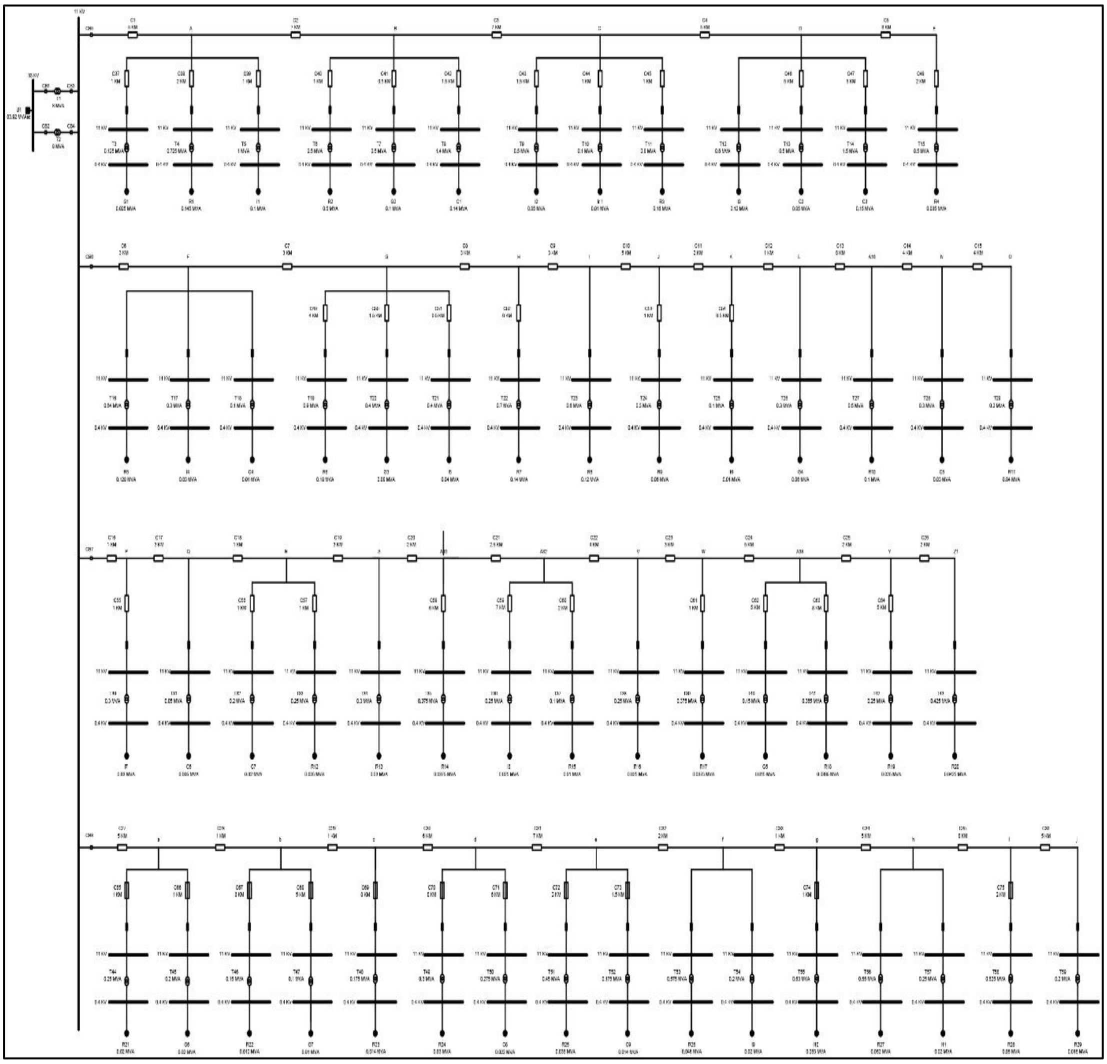

Fig. 3.2: Single line diagram of 33/11KV Udipur Substation feeders.

3.4 Cases of Analysis

Three cases have been analyzed. The descriptions of each case are provided below:

Base Case: Reliability analysis without DG integration.

Evaluation of reliability indices mainly SAIFI, SAIDI and EENS without integration of Distributed Generation has been considered for base case. A reliability analysis was conducted in ETAP 19.0.1 for RBTS bus-2 distribution system and 33/11KV Udipur distribution system, focusing on modelling without Distributed Generation (DG) connectivity. The analysis included the failure rates and MTTR data for the equipment, along with the number of customers and average load specified in the reference paper for the RBTS Bus-2 distribution system and the analysis incorporated the failure rates, MTTR data for the equipment's, as well as the number of customers and average load sourced from NEA Lamjung Distribution Center for 33/11KV Udipur distribution system. The improvements in later cases of analysis have been compared to the base case in terms of indices SAIFI, SAIDI, and EENS.

Case I: Analysis with DG integration by hit and trial method to determine the optimal location.

To ascertain the best injection point for Distributed Generation (DG), a 1 MW wind turbine was employed for the RBTS bus-2 distribution system, while a 0.5 MW wind turbine was utilized for the Udipur distribution system. The wind turbine was modeled as a Type-III DG source in generic mode within ETAP, featuring a failure rate of 0.03 failures per year and a repair time of 50 hours. It can inject both active and reactive power into the system. The process involved a hit-and-trial method, where the DG was injected at different test main points. Reliability indices values for SAIFI, SAIDI, and EENS were recorded after executing a reliability assessment in ETAP 19.0.1. The most optimal location was determined based on the position with the minimum SAIFI, SAIDI, and EENS.

Case II: Analysis with DG integration by ANN method to determine the optimal location.

In this case, the focus was on utilizing the feedforward backpropagation Neural Network (NN) among various ANN techniques, which is particularly effective for addressing fitting problems. This NN architecture comprises three layers: input, hidden, and output layers. To train and validate the network, input data patterns along with corresponding output data are essential. During the development phase of the ANN model, the available data is divided into three sets. Approximately 70% of the data is allocated for training the network, 15% is reserved for validation purposes, and the remaining 15% is used specifically for testing the performance of the NN.

In this study, the research involves employing the tan-sigmoid transfer function within both the hidden and output layers of the neural network. Specifically, for RBTS Bus-2 and the 33/11KV Udaipur Substation feeders, the hidden layers consist of 10 and 20 neurons respectively, while there is 1 neuron in the output layer and 3 neurons in the input layer. The feedforward backpropagation network is trained using the Levenberg-Marquardt algorithm, which iteratively updates the weights and biases to optimize network performance. The primary objective was to minimize the Mean Squared Error (MSE) between the actual and desired output values. The MSE served as a continuous stochastic optimization metric, guiding the network towards more accurate predictions and improved performance.

$$\mathrm{MSE} = \frac{1}{n} \sum_{i=1}^{n} (O_i - O_k)^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.1)$$

Where, Oi is the output obtained of the i^{th} pattern, O_k is the desired output of the the i^{th} pattern and n is the count of patterns.

For RBTS bus-2 distribution system to determine optimal location of DG by ANN method, DG was injected at different distances ranging from 20% to 100% for 14 Main points along their respective feeders from which we acquired 70 numbers of corresponding data for SAIFI, SAIDI and EENS. For 33/11KV Udipur distribution system in order to determine optimal location of DG by ANN method, Distributed Generation (DG) was injected at different distances ranging from 25% to 100% for 36 numbers of Main points along their respective feeders from which 144 numbers of training data corresponding to SAIFI, SAIDI and EENS from ETAP 19.0.1 simulation output was acquired for training purpose. Levenberg- Marquardt algorithm was adopted for training the network. This algorithm takes less time as training process automatically stops when generalizations stop improving as indicated by increase in Mean Square Error of validation samples. Out of total training datasets, 70% was used for training purpose, 15% for validation and remaining 15% for testing purpose. Lower value of MSE signified average squared difference between targets and outputs were lower which was preferred. Regression value close to unity was preferred which signified that there was Close relationship between target and output. Number of hidden layers were taken so as to have better convergence, lower value of MSE and Regression value close to unity. Outputs obtained for optimal locations after training on MATLAB R2021a ANN training toolbox were again validated with analytic approach in ETAP 19.0.1. Optimal location was identified based on the minimum value of SAIFI, SAIDI and EENS values of validation location obtained from injecting DG at respective location and performing reliability assessment in ETAP 19.0. 1.

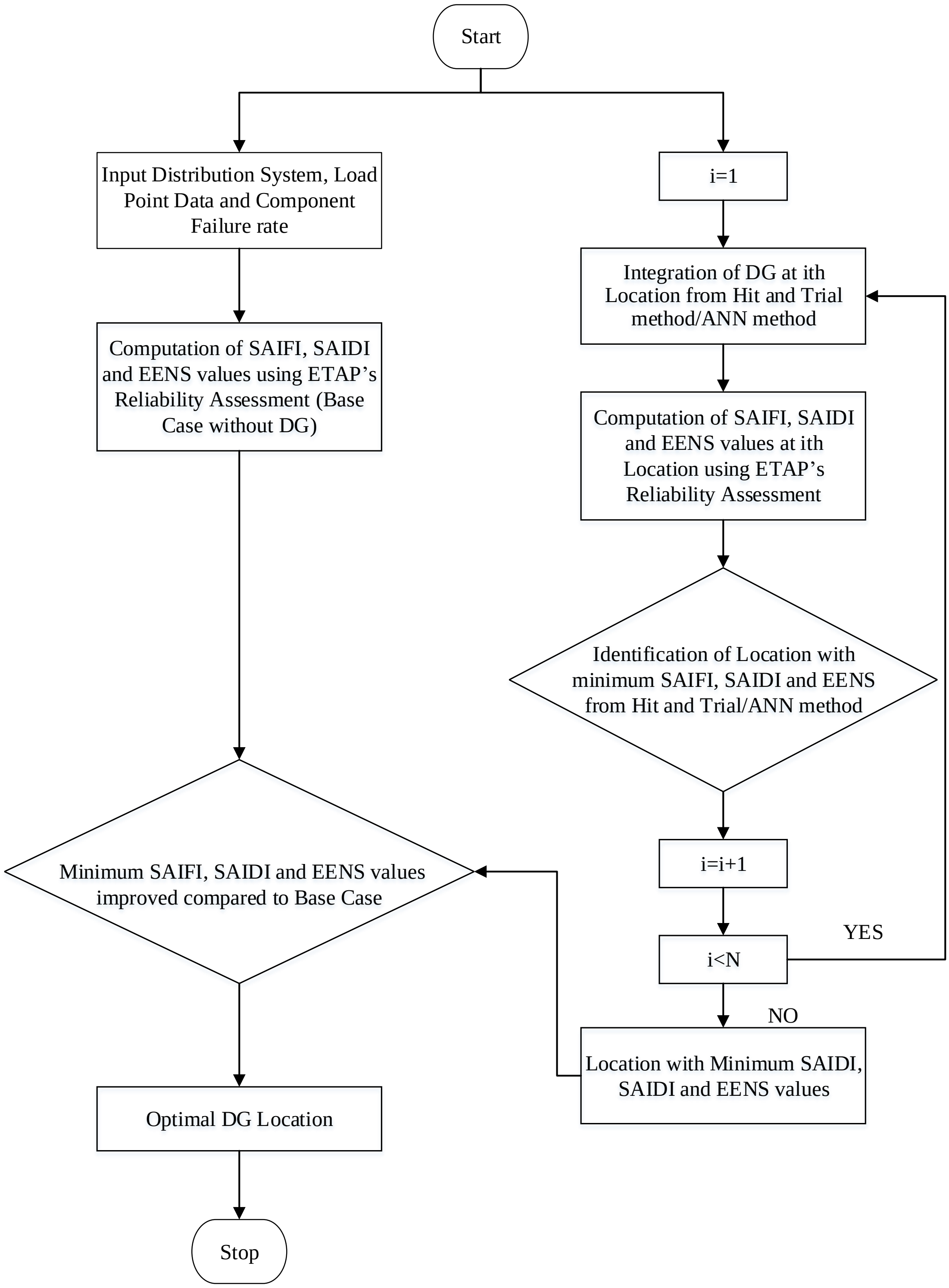

Fig. 3.3: Flowchart of Methodology

CHAPTER FOUR: RESULTS AND DISCUSSION

The aim of this thesis is to improve distribution system reliability through the strategic positioning of Distributed Generation. So, first target is to analyze the system in the base case scenario, which is without placement of the Distributed generation. Analysis is done in RBTS Bus-2 distribution system and 33/11KV Udipur distribution system Nepal, NEA and the parameters noted below has been studied in the base case scenario.

- System Average Interruption Frequency Index (SAIFI)
- System Average Interruption Duration Index (SAIDI)
- Expected Energy Not Supplied (EENS)
- Customer Average Interruption Duration Index (CAIDI)
- Average Service Availability Index (ASAI)
- Average Service Unavailability Index (ASUI)
- Average Energy Not Supplied (AENS)

4.1 RBTS BUS-2 Distribution System

4.1.1 Base Case: Reliability analysis without DG connection.

A reliability analysis was conducted in ETAP 19.0.1 for RBTS bus-2 distribution system, focusing on modelling without Distributed Generation (DG) connectivity. The analysis incorporated the provided failure rates, MTTR data for the equipment's, as well as the number of customers and average load in the reference paper. The findings of this analysis are outlined in Table 4.1, while the simulation results from ETAP are illustrated in Fig. 4.1. This modelling approach allows for an evaluation of the reliability and performance of RBTS bus-2 under normal operating conditions without the influence of DG system.

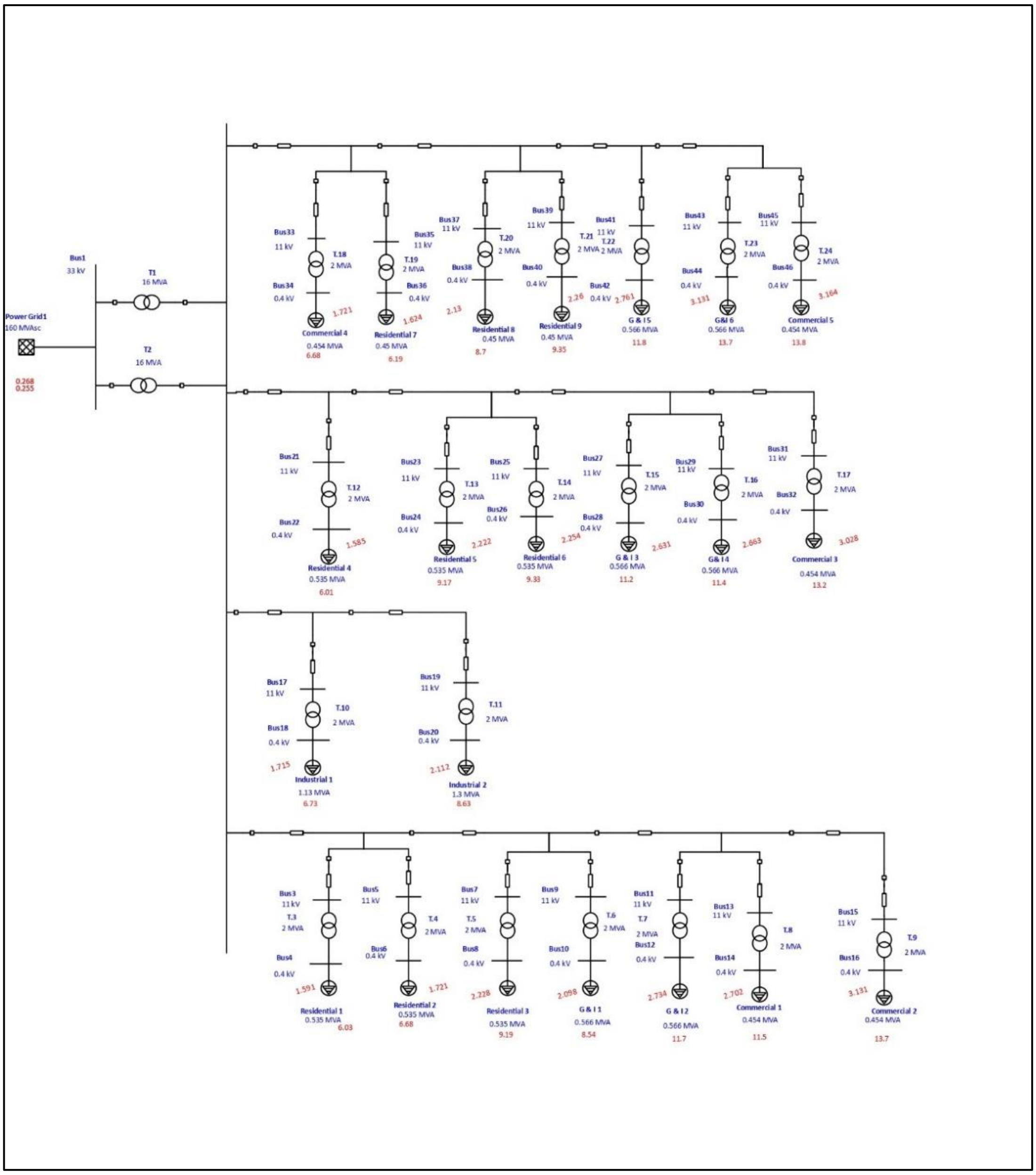

Fig. 4.1: RBTS BUS-2 Distribution system without DG connection simulation.

Table 4.1: Summary of Reliability metrics without DG connection.

S. N	Reliability Metrics	Outcomes
1	SAIFI (Interruptions/ Customer/ Year)	1.9772
2	SAIDI (hours/ Customer/ Year)	7.9509
3	EENS (MWhr/ Year)	114.089
4	CAIDI (Hours/ Customer interruptions)	4.021
5	ASAI (p.u)	0.9991
6	ASUI (p.u)	0.00091
7	AENS (MWhr/ Customer/ Year)	0.0608

4.1.2 Case I: Injecting DG at different locations to determine the optimal location.

To determine the optimal location for injecting Distributed Generation (DG), a wind turbine with a capacity of 1MW was used. The wind turbine was modeled as a Type-III DG source in generic mode within ETAP, has a failure rate of 0.03 failures per year and a repair time of 50 hours. It can inject both active and reactive power into the system. The process involved hit and trial method, where the DG was injected at different test Main points and optimal location by hit and trial method was found to be at point A (Main point 14). Summary of SAIFI, SAIDI and EENS values for DG injection at different Main points for optimal location are shown below in the Table 4.2 as well as in Fig. 4.2:

Table 4.2:SAIFI, SAIDI, EENS Values with DG connected at different Main points

DG injection points	SAIFI	SAIDI	EENS
A	1.5870	7.0251	97.619
B	1.7134	7.6499	110.575
C	1.5962	7.0692	98.991
D	1.6031	7.1022	104.103
E	1.7214	7.6810	107.470
F	1.6429	7.3025	99.455
G	1.6456	7.316	100.596

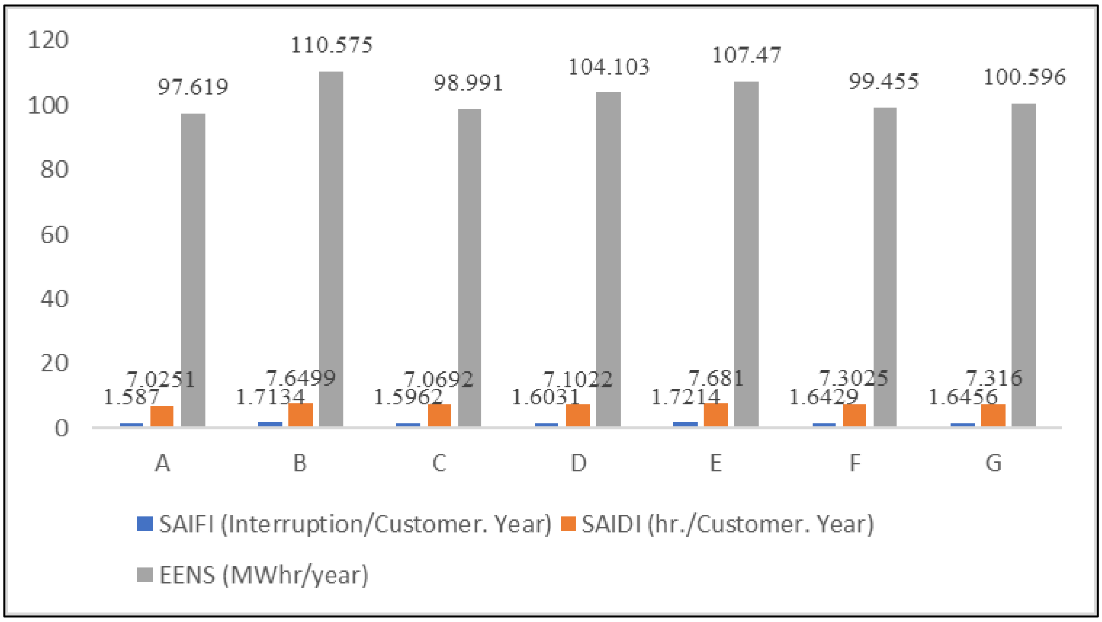

Fig. 4.2: SAIFI, SAIDI and EENS values for DG Penetration at different Main Points

The results obtained from the ETAP simulation, which analyzed the impact of injecting Distributed Generation (DG) at various locations, are presented in Table 4.2. The simulation identified the optimal location for DG injection as Main Point 14 (MP14) at point A, which yielded the lowest values for SAIFI, SAIDI, and EENS. Specifically, the optimal SAIFI was found to be 1.5870 interruptions per customer per year, the SAIDI was found to be 7.0251 hours per customer per year, and the EENS was found to be 97.619 MWh per year. Fig. 4.3 shows the simulation result for the DG integration at optimal location A (MP14) whereas Table 4.3 shows the Reliability indices obtained from ETAP simulation results for the DG connection at optimal location.

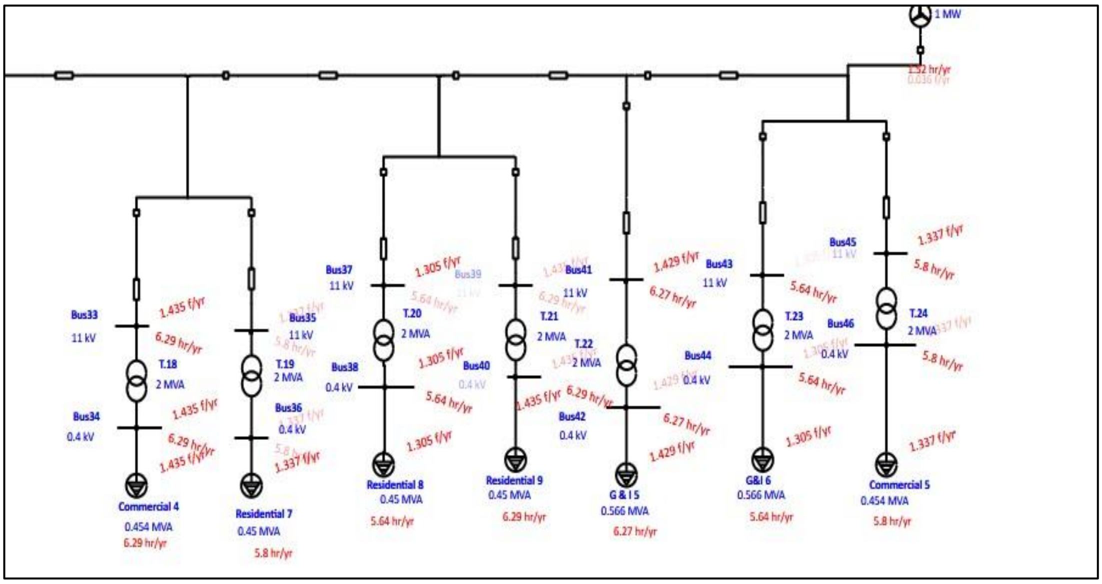

Fig. 4.3: Simulation result with DG connection at optimal point A

Table 4.3: Summary of Reliability analysis with DG at optimal point A.

S. N	Reliability Metrics	Outcomes
1	SAIFI (Interruptions/ Customer/Year)	1.5870
2	SAIDI (Hours/ Customer/Year)	7.0251
3	EENS (MWhr/ Year)	97.619
4	CAIDI (Hours/ Customer interruptions)	4.427
5	ASAI (p.u.)	0.9992
6	ASUI (p.u.)	0.00080
7	AENS (MWhr/ Customer. Year)	0.0520

4.1.3 Case II: ANN to determine optimal location of DG

By injecting Distributed Generation (DG) at different distances ranging from 20% to 100% for 14 numbers of Main points along their respective feeders, 70 numbers of corresponding data for SAIFI, SAIDI and EENS from ETAP simulation outputs was acquired for training purpose as tabulated in Table 4.4.

Table 4.4: Training Dataset for RBTS BUS-2 Distribution System

S. N	Main points Number	Number of customers	Loads (MVA)	Distance from feeder (KM)	SAIFI	SAIDI	EENS
1	MP1	420	1.07	0.15	1.7135	7.6492	110.603
2	MP1	420	1.07	0.3	1.7135	7.6492	110.603
3	MP1	420	1.07	0.45	1.7135	7.6492	110.603
4	MP1	420	1.07	0.6	1.7135	7.6492	110.603
5	MP1	420	1.07	0.75	1.7131	7.6489	110.600
6	MP2	201	1.101	0.9	1.6520	7.3468	104.252
7	MP2	201	1.101	1.05	1.6520	7.3468	104.252
8	MP2	201	1.101	1.2	1.6520	7.3468	104.252
9	MP2	201	1.101	1.35	1.6520	7.3468	104.252
10	MP2	201	1.101	1.5	1.6519	7.3466	104.25
11	MP3	11	1.02	1.65	1.6456	7.316	100.597
12	MP3	11	1.02	1.8	1.6456	7.316	100.597
13	MP3	11	1.02	1.95	1.6456	7.316	100.597
14	MP3	11	1.02	2.1	1.6456	7.316	100.597
15	MP3	11	1.02	2.25	1.6456	7.316	100.596
16	MP4	10	0.454	2.37	1.6429	7.3025	99.455
17	MP4	10	0.454	2.49	1.6429	7.3025	99.455
18	MP4	10	0.454	2.61	1.6429	7.3025	99.455
19	MP4	10	0.454	2.73	1.6429	7.3025	99.455
20	MP4	10	0.454	2.85	1.6429	7.3025	99.455
21	MP5	1	1.13	0.15	1.7216	7.6823	110.668

S. N	Main points Number	Number of customers	Loads (MVA)	Distance from feeder (KM)	SAIFI	SAIDI	EENS
22	MP5	1	1.13	0.3	1.7216	7.6823	110.668
23	MP5	1	1.13	0.45	1.7216	7.6823	110.668
24	MP5	1	1.13	0.6	1.7216	7.6823	110.668
25	MP5	1	1.13	0.75	1.7216	7.6823	110.666
26	MP6	1	1.3	0.87	1.7214	7.6810	107.472
27	MP6	1	1.3	0.99	1.7214	7.6810	107.472
28	MP6	1	1.3	1.11	1.7214	7.6810	107.472
29	MP6	1	1.3	1.23	1.7214	7.6810	107.472
30	MP6	1	1.3	1.35	1.7214	7.6810	107.470
31	MP7	200	0.535	0.15	1.7138	7.6508	110.596
32	MP7	200	0.535	0.3	1.7138	7.6508	110.596
33	MP7	200	0.535	0.45	1.7138	7.6508	110.596
34	MP7	200	0.535	0.6	1.7138	7.6508	110.596
35	MP7	200	0.535	0.75	1.7135	7.6505	110.593
36	MP8	400	1.07	0.91	1.6033	7.1024	104.105
37	MP8	400	1.07	1.07	1.6033	7.1024	104.105
38	MP8	400	1.07	1.23	1.6033	7.1024	104.105
39	MP8	400	1.07	1.39	1.6033	7.1024	104.105
40	MP8	400	1.07	1.55	1.6031	7.1022	104.103
41	MP9	2	1.132	1.67	1.5984	7.0800	99.920
42	MP9	2	1.132	1.79	1.5984	7.0800	99.920
43	MP9	2	1.132	1.91	1.5984	7.0800	99.920
44	MP9	2	1.132	2.03	1.5984	7.0800	99.920
45	MP9	2	1.132	2.15	1.5984	7.0800	99.918
46	MP10	10	0.454	2.3	1.5962	7.0692	98.991
47	MP10	10	0.454	2.45	1.5962	7.0692	98.991
48	MP10	10	0.454	2.6	1.5962	7.0692	98.991

S. N	Main points Number	Number of customers	Loads (MVA)	Distance from feeder (KM)	SAIFI	SAIDI	EENS
49	MP10	10	0.454	2.75	1.5962	7.0692	98.991
50	MP10	10	0.454	2.9	1.5962	7.0692	98.991
51	MP11	210	0.904	0.16	1.7137	7.6503	110.578
52	MP11	210	0.904	0.32	1.7137	7.6503	110.578
53	MP11	210	0.904	0.48	1.7137	7.6503	110.578
54	MP11	210	0.904	0.64	1.7137	7.6503	110.578
55	MP11	210	0.904	0.8	1.7134	7.6499	110.575
56	MP12	400	0.9	0.95	1.5947	7.0611	104.044
57	MP12	400	0.9	1.1	1.5947	7.0611	104.044
58	MP12	400	0.9	1.25	1.5947	7.0611	104.044
59	MP12	400	0.9	1.4	1.5947	7.0611	104.044
60	MP12	400	0.9	1.55	1.5945	7.0608	104.041
61	MP13	1	0.566	1.7	1.5900	7.0397	100.120
62	MP13	1	0.566	1.85	1.5900	7.0397	100.120
63	MP13	1	0.566	2	1.5900	7.0397	100.120
64	MP13	1	0.566	2.15	1.5900	7.0397	100.120
65	MP13	1	0.566	2.3	1.5899	7.0397	100.118
66	MP14	11	1.02	2.42	1.5870	7.0251	97.620
67	MP14(A)	11	1.02	2.54	1.5870	7.0251	97.620
68	MP14	11	1.02	2.66	1.5870	7.0251	97.620
69	MP14	11	1.02	2.78	1.5870	7.0251	97.620
70	MP14	11	1.02	2.9	1.5870	7.0251	97.619

The Levenberg-Marquardt algorithm was employed to train the neural network using the ANN training toolbox in MATLAB R2021a. Out of total training datasets, 70% was used for training purpose, 15% for validation and remaining 15% for testing purpose. Lower value of MSE signified that average squared difference between targets and outputs were lower which was preferred as shown in Fig.4.4. Regression value close to unity was preferred which showed the close relationship between target and output as shown in Fig. 4.5. Number of hidden layers were taken 10 so as to have better convergence, lower value of MSE and Regression value close to unity. Overall Regression value was found to be 0.98806 after training on MATLAB as shown in Fig. 4.5. Error Histogram Diagram is shown in Fig 4.6 which shows that errors between target and output were within the acceptable limit.

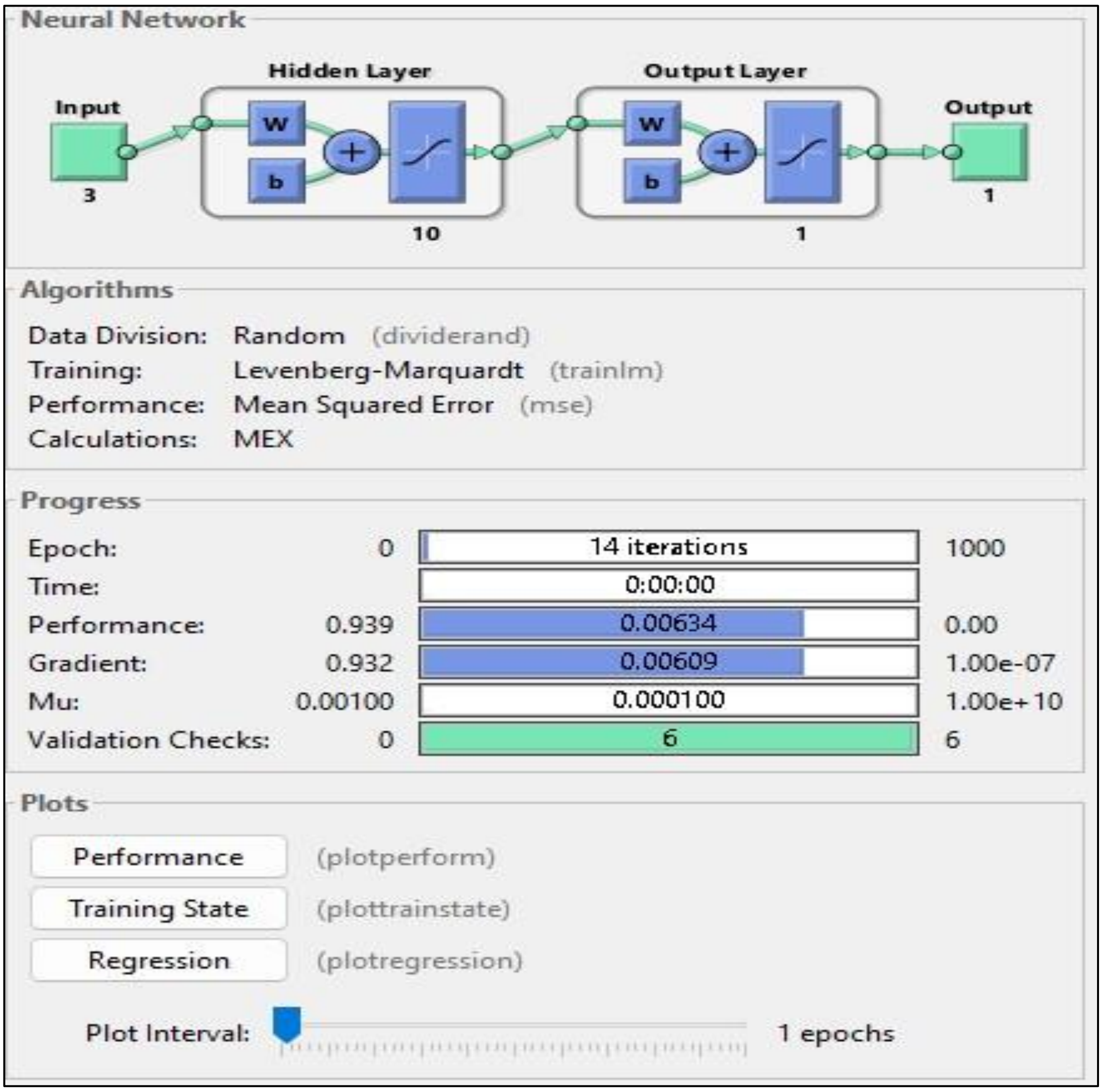

Fig. 4.4: Neural Network training on MATLAB by Levenberg-Marquardt Method.

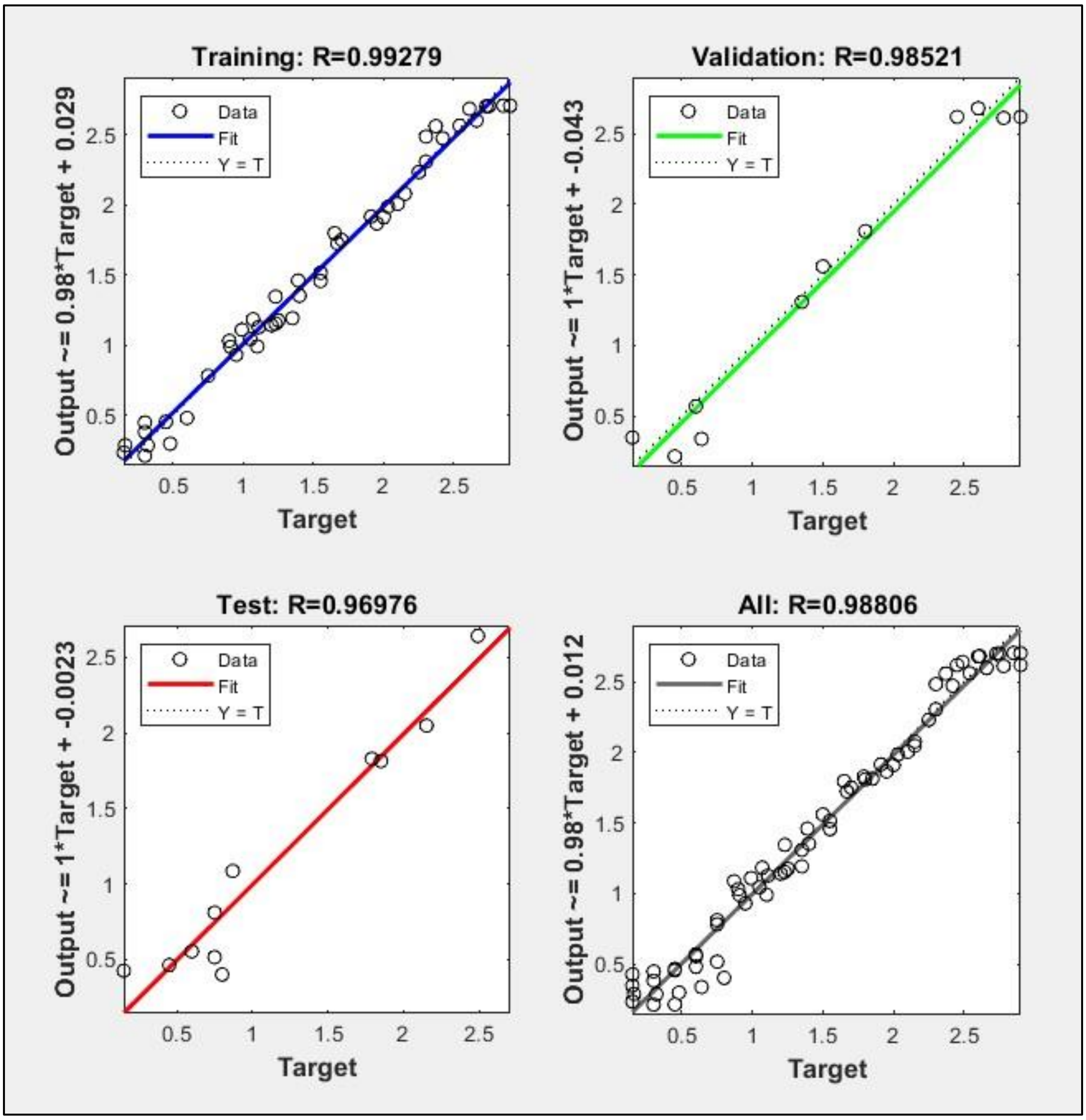

Fig. 4.5: Regression result after training of RBTS BUS-2 Distribution Network.

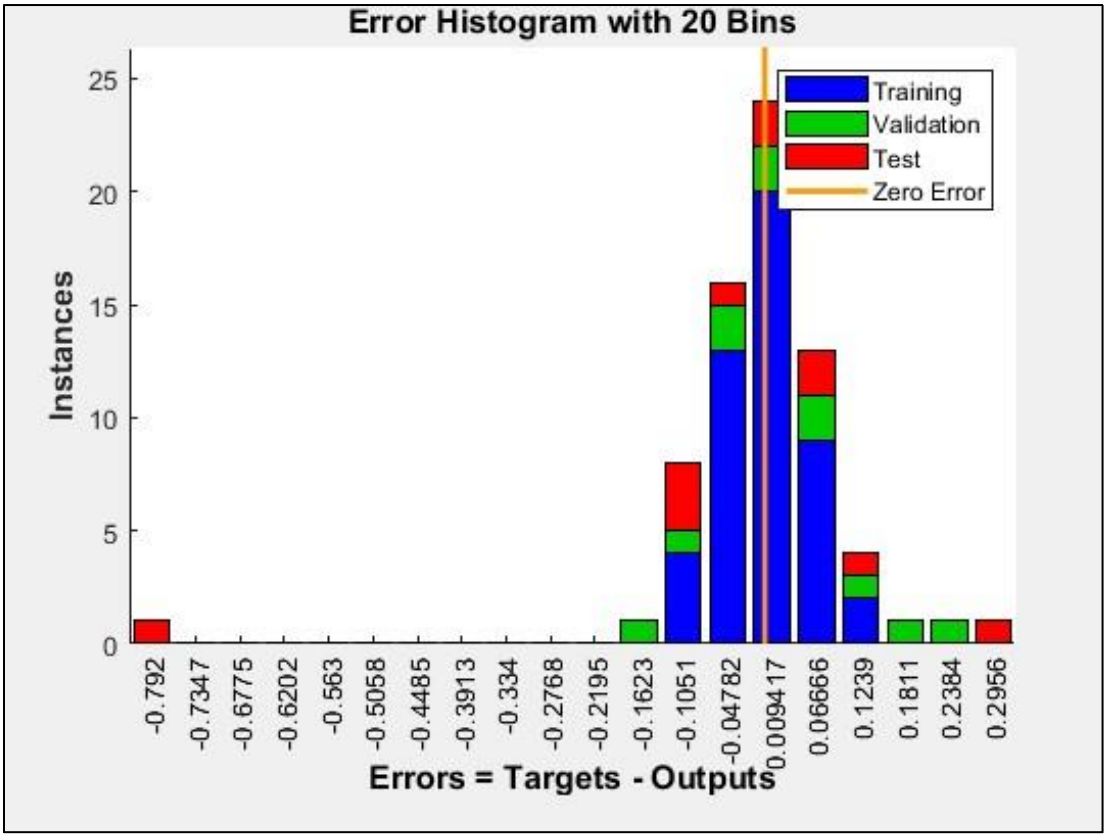

Fig. 4.6: Error Histogram diagram for ANN training of RBTS BUS-2 Distribution System

Outputs for optimal locations from training on MATLAB R2021a can be denoted as Location 1, Location 2 and Location 3 near main points 7,8 and 14 at a distance of 0.48 KM, 1.51KM and 2.62KM from their feeders respectively.

4.1.3.1 DG integration in ETAP at Validation Location 1.

The DG was positioned close to Main point 7, approximately 0.48 KM away from the feeder, based on the optimal location determined from the training results. Fig. 4.7 illustrates the placement of the DG. Following the placement of the DG at the designated distance, as depicted in Fig. 4.8, A reliability evaluation was carried out, and the metrics were recorded. Table 4.5 demonstrates a slight decrease in the reliability indices compared to the absence of DG installation, indicating a little enhancement in reliability.

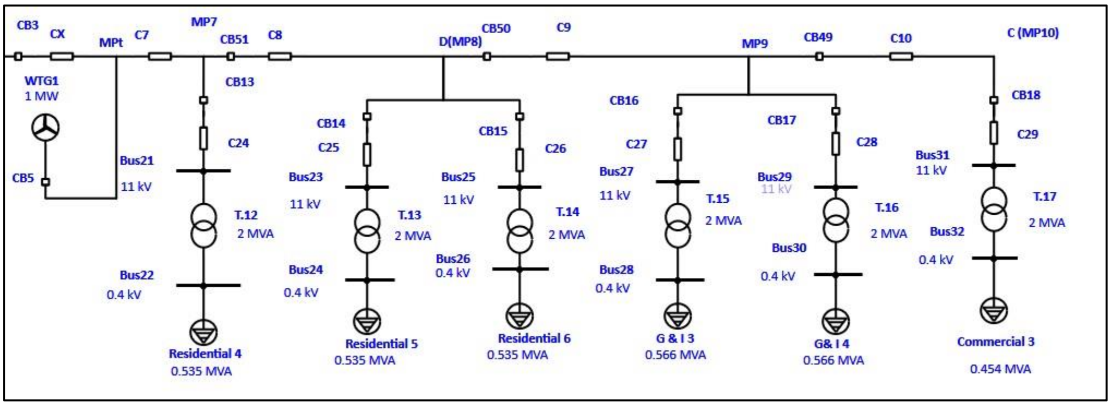

Fig. 4.7:DG integration at Validation Location 1.

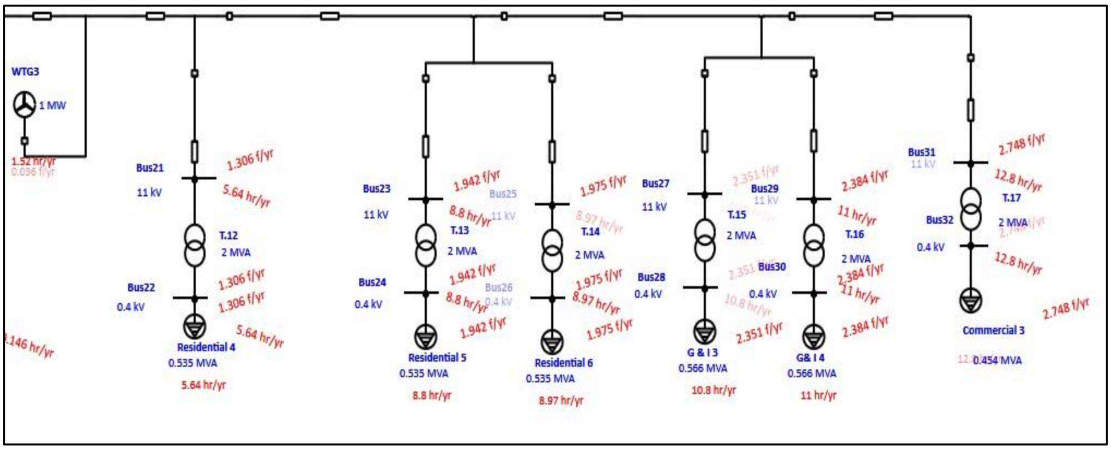

Fig. 4.8: Simulation result of DG connection at Validation Location 1.

Table 4.5: Summary of Reliability metrics.

S. N	Reliability Metrics	Without DG	DG at Validation Location 1
1	SAIFI	1.9772	1.7138
2	SAIDI	7.9509	7.6508
3	EENS	114.089	110.596

4.1.3.2 DG integration in ETAP at Validation Location 2

The DG was positioned close to Main point 8, situated approximately 1.51 KM from the feeder, following the optimal location determined from the training results Fig. 4.9 depicts the DG placement. Following the placement of the DG at the designated distance, as shown in Fig. 4.10, a reliability evaluation was conducted, and the metrics were recorded. Table 4.6 indicates a slight decrease in the reliability indices compared to the placement of DG at Validation Location 1, suggesting a minor improvement in reliability.

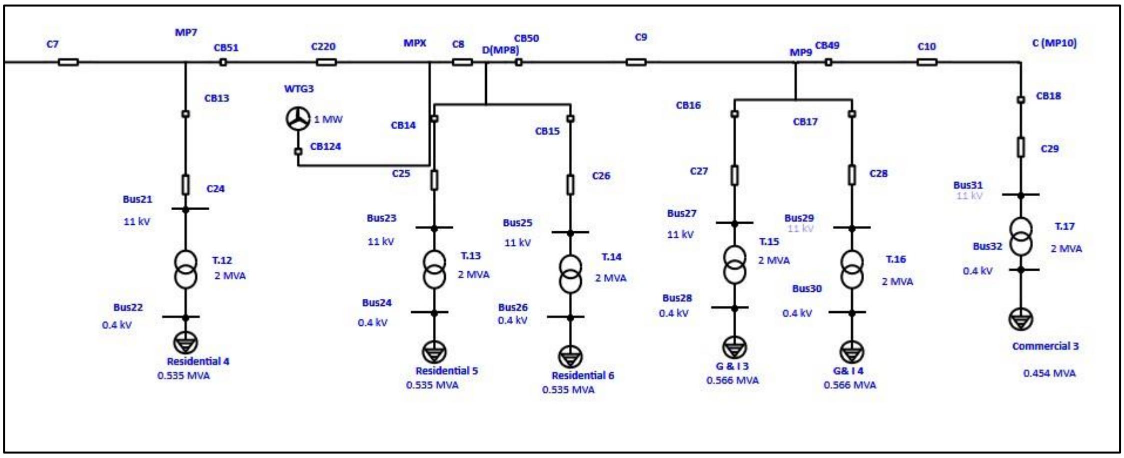

Fig. 4.9:DG integration at Validation Location 2.

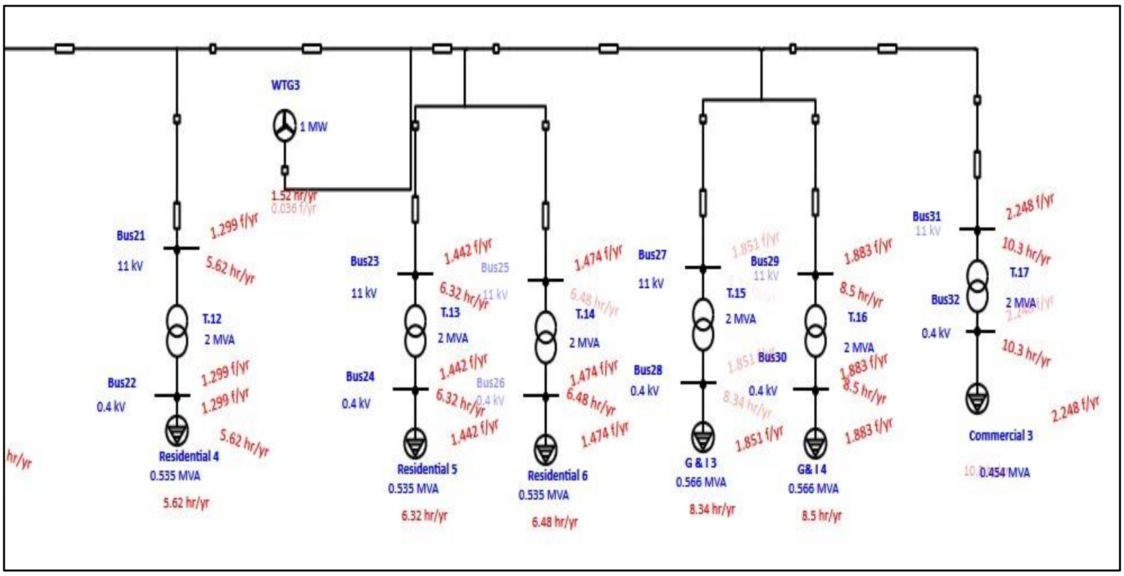

Fig. 4.10: Simulation result of DG connection at Validation Location 2

Table 4.6: Summary of Reliability metrics.

S. N	Reliability Metrics	Without DG	DG at Validation Location 2
1	SAIFI	1.9772	1.6033
2	SAIDI	7.9509	7.1024
3	EENS	114.089	104.105

4.1.3.3 DG integration in ETAP at Validation Location 3s

The DG was positioned near Main point 14, approximately 2.62 KM from the feeder, according to the optimal location identified from the training results. Fig. 4.11 shows the DG placement. After installing the DG at the specified distance, as depicted in Fig. 4.12, a reliability evaluation was performed, and the metrics were documented. Table

4.7 highlights the most substantial reduction in reliability metrics compared to previous DG placements at earlier validation locations. From the recorded indices, it can be concluded that location 3, predicted by the ANN as the optimal DG placement site, as shown in Table 4.8, was confirmed. The reliability metrics showed further reduction, leading to improved reliability.

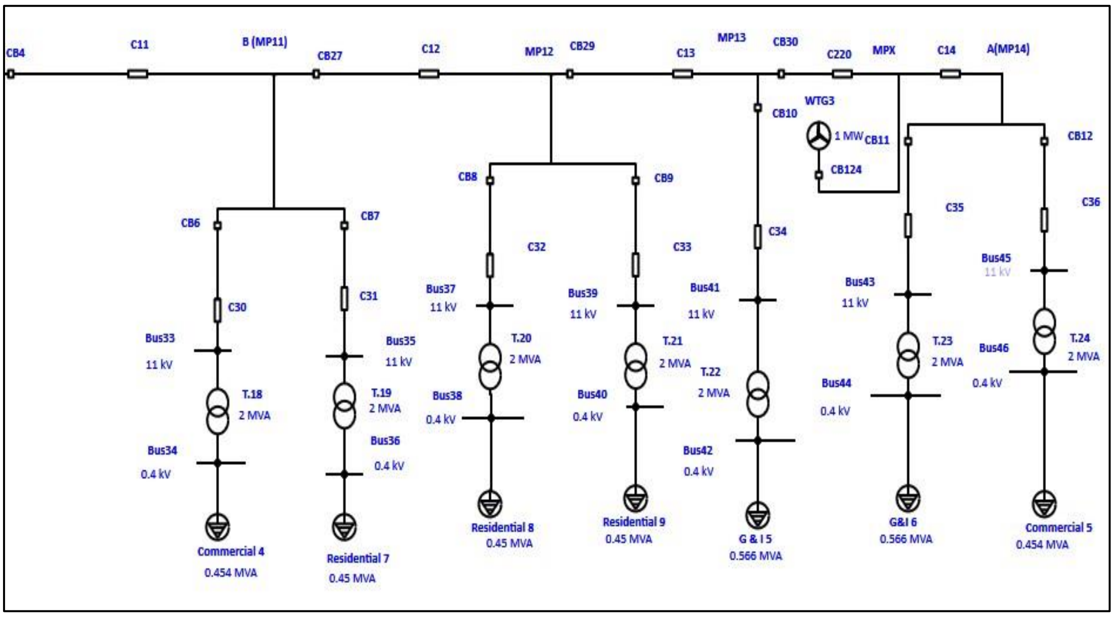

Fig. 4.11: DG integration at Validation Location 3.

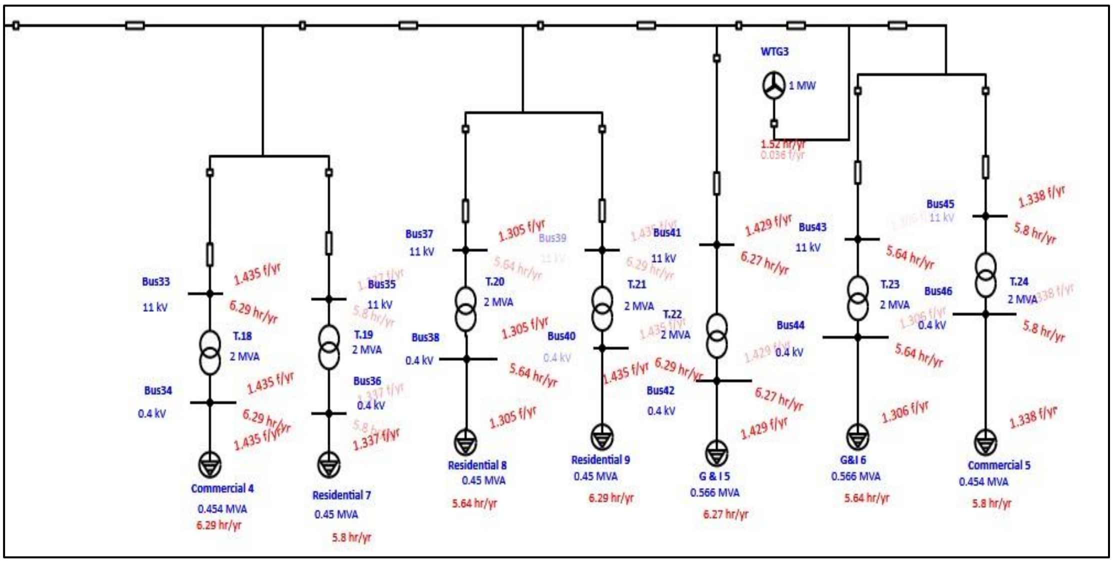

Fig. 4.12: Simulation result of DG connection at Validation Location 3.

Table 4.7: Summary of Reliability metrics at validation location.

S. N	Reliability Metrics	Outcomes
1	SAIFI (Interruptions/ Customer/ Year)	1.5870
2	SAIDI (Hours/ Customer/Year)	7.0251
3	EENS (MWhr/ Year)	97.620
4	CAIDI (Hours/ Customer interruptions)	4.427
5	ASAI (p.u.)	0.9992
6	ASUI (p.u.)	0.00080
7	AENS (MWhr/ Customer/ Year)	0.0520

Table 4.8: SAIFI, SAIDI and EENS Values at Validation Locations.

S. N	System Indices	Without DG	Validation Location 1	Validation Location 2	Validation Location 3
1	SAIFI	1.9772	1.7138	1.6033	1.5870
2	SAIDI	7.9509	7.6508	7.1024	7.0251
3	EENS	114.089	110.596	104.105	97.620

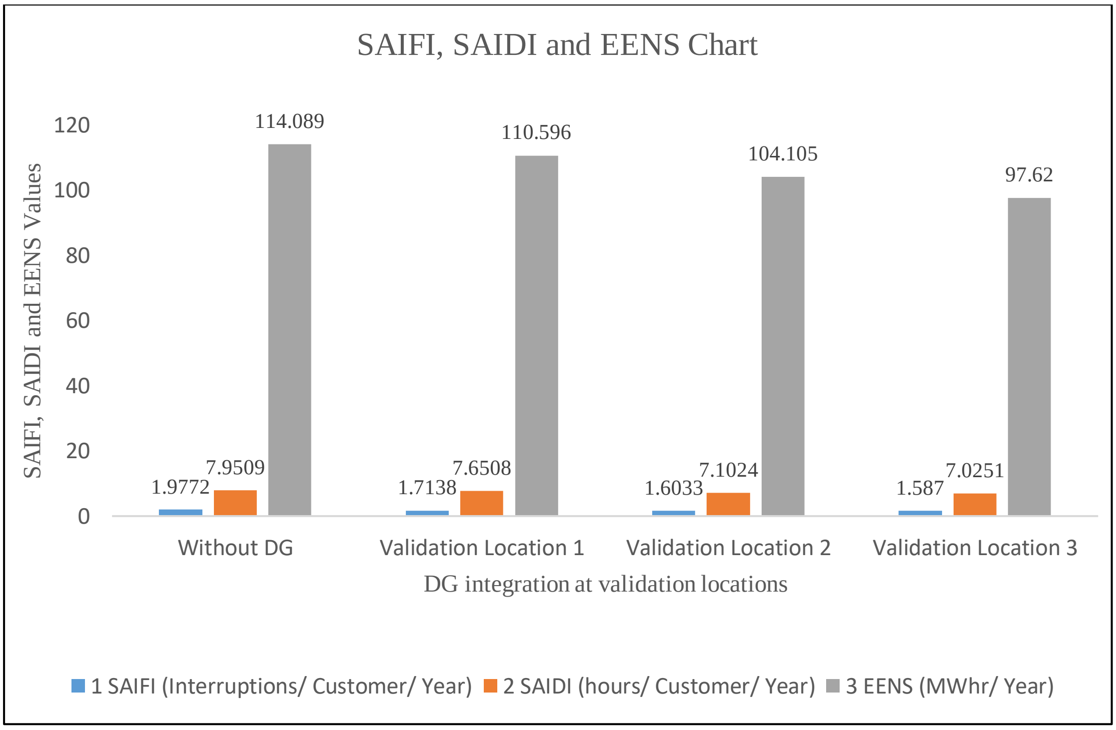

Fig. 4.13: SAIFI, SAIDI and EENS Chart at Validation Locations.

Optimal location for DG integration is at 2.62KM from feeder toward MP14 of feeder 4 which clearly shows that there is reduction in SAIFI, SAIDI and EENS values by approximately 20%, 12% and 15% respectively.

4.2 33/11KV Udipur Distribution System

Udipur Substation of Lamjung District under the NEA has four outgoing radial feeders of rural areas. Four feeders radial and lateral lengths along with average load and number of customers, tripping frequencies, Outage Durations are shown in Table 4.9. Failure rates and MTTR for four outgoing feeders were calculated based on the tripping frequency and outage duration data sourced from NEA Lamjung Distribution Centre as shown in Table 4.10.

Table 4.9: Feeders details.

S. N	Name of Feeder	Number of Customers	Average Load (MVA)	Radial Length (KM)	Lateral Length (KM)	Total Length (KM)
1	Besishahar	14131	1.590	24	22.5	47
2	Bhoteodar	9041	1.000	36	13.5	50
3	Okhari	5324	0.377	28.5	32.5	61
4	Nayagaun	7958	0.445	41	43.5	85
	Total	**36454**	**3.412**	**129.5**	**112**	**241.5**

Table 4.10: Feeders Tripping frequency and Outage duration.

S. N	Name of Feeder	Number of tripping	Repair time	Operation hour	Failure rate (Number of tripping/O.H)	Mean time to Repair
1	Besishahar	57	38.966	8721.034	0.0065	0.68
2	Bhoteodar	69	52.183	8707.817	0.0079	0.76
3	Okhari	88	98.55	8661.45	0.0102	1.12
4	Nayagaun	100	146.633	8613.367	0.0116	1.47

4.2.1 Base Case: Reliability Analysis without DG Connection.

A reliability analysis was conducted in ETAP 19.0.1 for 33/11KV Udipur distribution system, focusing on modelling without Distributed Generation (DG) connectivity. The evaluation included the equipment failure rates and MTTR data, along with the customer count and average load, sourced from the NEA Lamjung Distribution Center. The result of this analysis is summarized in the Table 4.11 and ETAP simulation result in Fig.4.14. This modeling approach facilitates the assessment of both reliability and performance of 33/11KV Udipur distribution system under normal operating conditions without the influence of DG system.

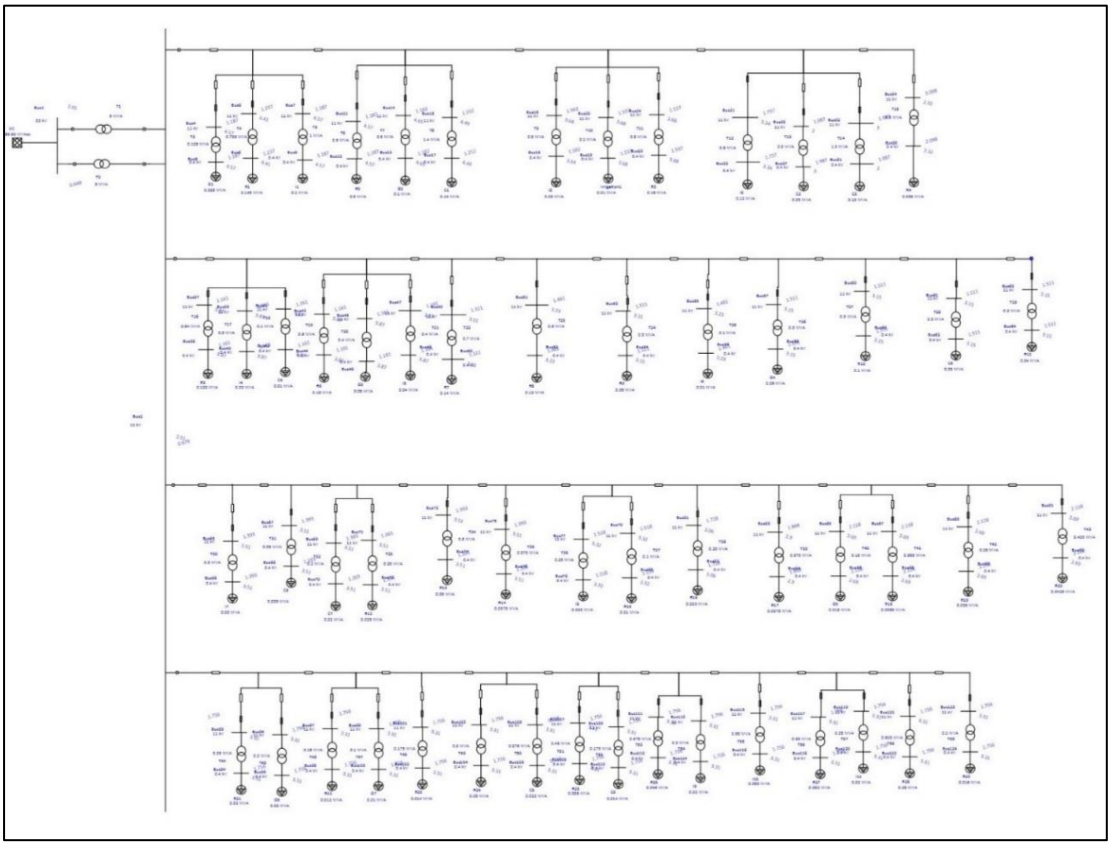

Fig. 4.14: Simulation result of Udipur Distribution system without DG connection.

Table 4.11: Summary of reliability metrics without DG connection.

S. N	Reliability Metrics	Outcomes
1	SAIFI (Interruptions/ Customer/Year)	1.4957
2	SAIDI (hours/ Customer/ Year)	5.2901
3	EENS (MWhr/ Year)	15.330

S. N	Reliability Metrics	Outcomes
4	CAIDI (Hours/ Customer interruption)	3.5370
5	ASAI (pu)	0.9994
6	ASUI (pu)	0.00060
7	AENS (MWhr/ Customer/ Year)	0.0004

4.2.2 Case I: Determining the Optimal Location by Injecting DG at Various Sites.

To determine the optimal location for injecting Distributed Generation (DG), a wind turbine with a capacity of 0.5MW was used. The wind turbine was modeled as a Type-III DG source in generic mode within ETAP, has a failure rate of 0.03 failures per year and a repair time of 50 hours. It can inject both active and reactive power into the system. The process involved hit and trial method, where the DG was injected at different test Main points and optimal location by hit and trial method was found to be at point E (Main point 5) of Besisahar Feeder as shown in Fig.4.17. Table 4.12 presents a summary of SAIFI, SAIDI, and EENS values following DG injection at various main points to determine the optimal location.

Table 4.12:DG at various locations for hit and trial method

DG injection points	SAIFI	SAIDI	EENS
A	0.8403	3.8505	11.066
C	0.8017	3.8243	10.949
E	0.7786	3.8085	10.892
O	0.8041	3.8698	11.129
R	0.8449	3.9347	11.427
Z1	0.7892	3.8726	11.318
a	0.8435	3.9066	11.399
j	0.8435	3.9097	11.405

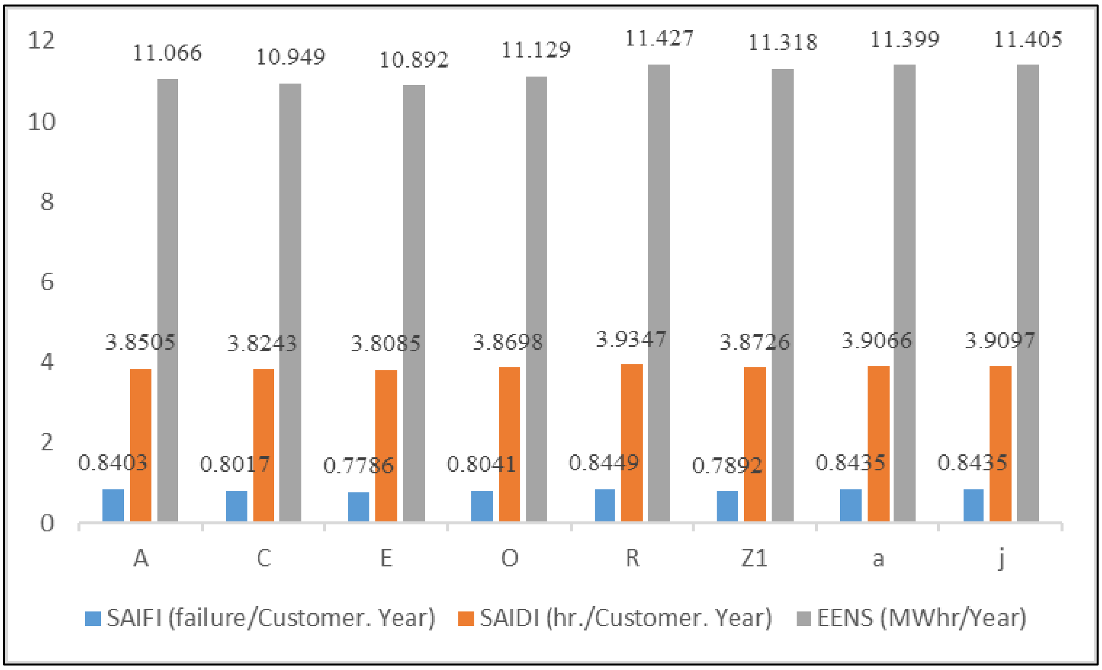

Fig. 4.15: SAIFI, SAIDI and EENS values for DG Penetration at different Main Points.

The results obtained from the ETAP simulation, which analyzed the impact of injecting Distributed Generation (DG) at various locations, are presented in Table 4.12. The simulation identified the optimal location for DG injection as Main Point 5 (MP5) at point E, which yielded the lowest values for SAIFI, SAIDI, and EENS. Specifically, the optimal SAIFI was found to be 0.7786 interruptions per customer per year, the SAIDI was found to be 3.8085 hours per customer per year, and the EENS was found to be 10.892 MWh per year. Fig. 4.16 shows the simulation result for the DG integration at optimal location E (MP5) whereas Table 4.13 shows the Reliability indices obtained from ETAP simulation results for the DG connection at optimal location.

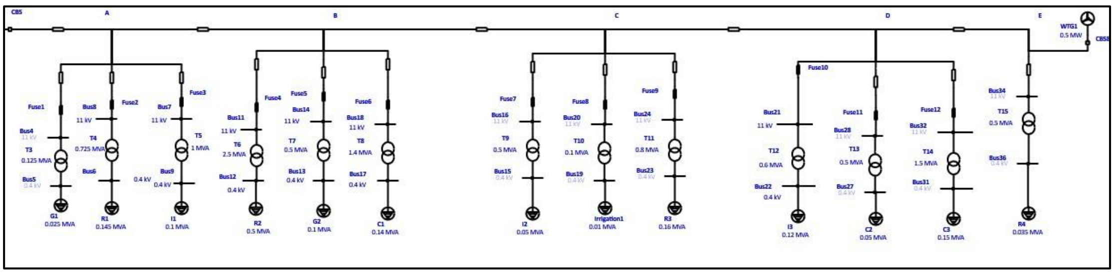

Fig. 4.16: DG placement at optimal location E.

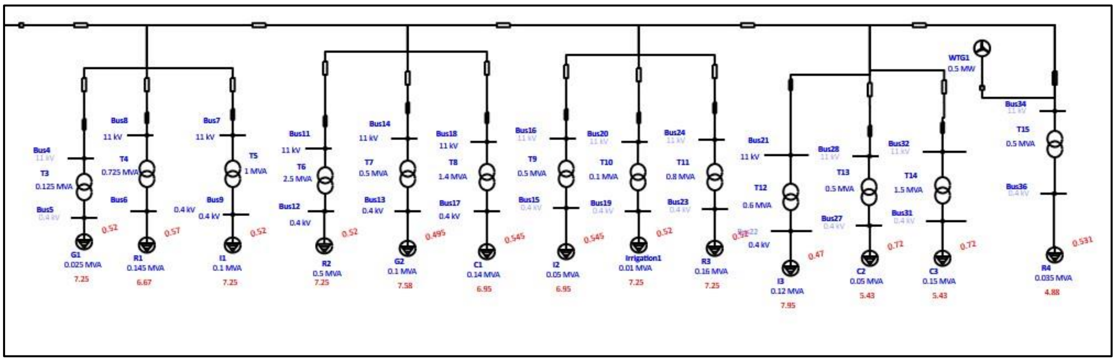

Fig. 4.17: Simulation result with DG connection at Optimal location E.

Table 4.13: Summary of Reliability metrics of DG placement at E

S. N	Reliability Metrics	Outcomes
1	SAIFI (Interruptions/ Customer/ Year)	0.7786
2	SAIDI (hours/ Customer/Year)	3.8085
3	EENS (MWhr/ Year)	10.892
4	CAIDI (hours/ Customer interruptions)	4.8910
5	ASAI (p.u.)	0.9996
6	ASUI (p.u.)	0.00043
7	AENS (MWhr/ Customer/ Year)	0.0003

4.2.3 Case II: ANN to determine optimal location of DG

By injecting Distributed Generation (DG) at different distances ranging from 25% to 100% for 36 numbers of Main points along their respective feeders, 144 numbers of corresponding data for SAIFI, SAIDI and EENS from ETAP simulation outputs was acquired for training purpose as tabulated in Table 4.14.

Table 4.14:Training datasets

S. N	Main points	Distance from feeder (KM)	Number of Customers	Average Load, MVA	SAIFI (f/Customer. Year)	SAIDI (hr/ Customer. Year)	EENS (MWhr/ Year)
1	1	1.25	2309	0.27	0.8407	3.8513	11.068
2	1	2.5	2309	0.27	0.8407	3.8513	11.068
3	1	3.75	2309	0.27	0.8407	3.8513	11.068
4	1	5	2309	0.27	0.8403	3.8505	11.066

S. N	Main points	Distance from feeder (KM)	Number of Customers	Average Load, MVA	SAIFI (f/Customer. Year)	SAIDI (hr/ Customer. Year)	EENS (MWhr/ Year)
5	2	6.75	7804	0.74	0.8407	3.8513	11.068
6	2	8.5	7804	0.74	0.8407	3.8513	11.068
7	2	10.25	7804	0.74	0.8407	3.8513	11.068
8	2	12	7804	0.74	0.8271	3.8415	11.034
9	3	13.75	2457	0.22	0.8311	3.8447	11.039
10	3	15.5	2457	0.22	0.8214	3.8382	11.010
11	3	17.25	2457	0.22	0.8118	3.8316	10.981
12	3	19	2457	0.22	0.8017	3.8243	10.949
13	4	20.25	48	0.32	0.7995	3.8232	10.939
14	4	21.5	48	0.32	0.7968	3.8214	10.926
15	4	22.75	48	0.32	0.7941	3.8196	10.914
16	4	24	48	0.32	0.7911	3.8170	10.898
17	5	25.5	1511	0.035	0.7883	3.8157	10.899
18	5	27	1511	0.035	0.7852	3.8136	10.898
19	5	28.5	1511	0.035	0.7821	3.8114	10.896
20	5	30	1511	0.035	0.7786	3.8085	10.892
21	6	0.75	1529	0.168	0.8297	3.8905	11.201
22	6	1.5	1529	0.168	0.8295	3.8902	11.200
23	6	2.25	1529	0.168	0.8292	3.8900	11.199
24	6	3	1529	0.168	0.8297	3.8903	11.2
25	7	3.75	2259	0.31	0.8297	3.8905	11.201
26	7	4.5	2259	0.31	0.8295	3.8902	11.200
27	7	5.25	2259	0.31	0.8292	3.8900	11.199
28	7	6	2259	0.31	0.8297	3.8903	11.2
29	8	6.75	1598	0.14	0.8243	3.8864	11.187
30	8	7.5	1598	0.14	0.8186	3.8820	11.173
31	8	8.25	1598	0.14	0.8130	3.8776	11.158

S. N	Main points	Distance from feeder (KM)	Number of Customers	Average Load, MVA	SAIFI (f/Customer. Year)	SAIDI (hr/ Customer. Year)	EENS (MWhr/ Year)
32	8	9	1598	0.14	0.8081	3.8739	11.146
33	9	9.75	1370	0.12	0.8043	3.8713	11.136
34	9	10.5	1370	0.12	0.8003	3.8681	11.125
35	9	11.25	1370	0.12	0.7963	3.8649	11.114
36	9	12	1370	0.12	0.7931	3.8625	11.105
37	10	13.25	685	0.06	0.7929	3.8625	11.105
38	10	14.5	685	0.06	0.7924	3.862	11.103
39	10	15.75	685	0.06	0.792	3.8615	11.102
40	10	17	685	0.06	0.7931	3.8625	11.105
41	11	17.5	1	0.01	0.7931	3.8628	11.106
42	11	18	1	0.01	0.7930	3.8626	11.106
43	11	18.5	1	0.01	0.7928	3.8624	11.105
44	11	19	1	0.01	0.7931	3.8625	11.105
45	12	19.25	1	0.06	0.7927	3.8625	11.105
46	12	19.5	1	0.06	0.792	3.8619	11.103
47	12	19.75	1	0.06	0.7914	3.8614	11.100
48	12	20	1	0.06	0.7909	3.8608	11.098
49	13	22	1141	0.1	0.7904	3.8605	11.097
50	13	24	1141	0.1	0.7897	3.8597	11.094
51	13	26	1141	0.1	0.7890	3.8589	11.091
52	13	28	1141	0.1	0.7909	3.8608	11.098
53	14	29	1	0.03	0.7908	3.8609	11.098
54	14	30	1	0.03	0.7904	3.8605	11.097
55	14	31	1	0.03	0.7901	3.8601	11.095
56	14	32	1	0.03	0.7909	3.8608	11.098
57	15	33	457	0.04	0.7908	3.8609	11.098
58	15	34	457	0.04	0.7904	3.8605	11.097

S. N	Main points	Distance from feeder (KM)	Number of Customers	Average Load, MVA	SAIFI (f/Customer. Year)	SAIDI (hr/ Customer. Year)	EENS (MWhr/ Year)
59	15	35	457	0.04	0.7901	3.8601	11.095
60	15	36	457	0.04	0.7909	3.8608	11.098
61	16	0.25	25	0.03	0.8317	3.9261	11.398
62	16	0.5	25	0.03	0.8316	3.9259	11.397
63	16	0.75	25	0.03	0.8316	3.9257	11.397
64	16	1	25	0.03	0.8317	3.9260	11.397
65	17	1.75	2	0.005	0.8316	3.9257	11.396
66	17	2.5	2	0.005	0.8313	3.9251	11.395
67	17	3.25	2	0.005	0.8311	3.9245	11.394
68	17	4	2	0.005	0.8317	3.9260	11.397
69	18	4.25	500	0.045	0.8317	3.9261	11.397
70	18	4.5	500	0.045	0.8316	3.9259	11.397
71	18	4.75	500	0.045	0.8316	3.9257	11.396
72	18	5	500	0.045	0.8317	3.9257	11.396
73	19	5.75	579	0.03	0.8316	3.9254	11.395
74	19	6.5	579	0.03	0.8313	3.9248	11.394
75	19	7.25	579	0.03	0.8311	3.9242	11.393
76	19	8	579	0.03	0.8317	3.9255	11.396
77	20	8.5	723	0.0375	0.8316	3.9254	11.396
78	20	9	723	0.0375	0.8315	3.9250	11.395
79	20	9.5	723	0.0375	0.8313	3.9247	11.394
80	20	10	723	0.0375	0.8317	3.9253	11.396
81	21	10.625	213	0.035	0.8286	3.9218	11.389
82	21	11.25	213	0.035	0.8254	3.9179	11.382
83	21	11.875	213	0.035	0.8222	3.9141	11.374
84	21	12.5	213	0.035	0.8197	3.9119	11.370
85	22	13.5	482	0.025	0.8150	3.9064	11.360

S. N	Main points	Distance from feeder (KM)	Number of Customers	Average Load, MVA	SAIFI (f/Customer. Year)	SAIDI (hr/ Customer. Year)	EENS (MWhr/ Year)
86	22	14.5	482	0.025	0.8102	3.9005	11.350
87	22	15.5	482	0.025	0.8053	3.8947	11.340
88	22	16.5	482	0.025	0.8017	3.8920	11.336
89	23	17.25	723	0.0375	0.7987	3.8885	11.330
90	23	18	723	0.0375	0.7956	3.8847	11.323
91	23	18.75	723	0.0375	0.7924	3.8808	11.316
92	23	19.5	723	0.0375	0.7902	3.8790	11.314
93	24	20.75	774	0.0515	0.7863	3.8743	11.305
94	24	22	774	0.0515	0.7824	3.8693	11.296
95	24	23.25	774	0.0515	0.7784	3.8643	11.287
96	24	24.5	774	0.0515	0.7759	3.8636	11.287
97	25	25	482	0.025	0.7759	3.8635	11.286
98	25	25.5	482	0.025	0.7757	3.8631	11.286
99	25	26	482	0.025	0.7756	3.8627	11.285
100	25	26.5	482	0.025	0.7759	3.8636	11.287
101	26	27	820	0.0425	0.7759	3.8635	11.286
102	26	27.5	820	0.0425	0.7757	3.8631	11.286
103	26	28	820	0.0425	0.7756	3.8627	11.285
104	26	28.5	820	0.0425	0.7759	3.8636	11.287
105	27	1.25	632	0.04	0.8295	3.8981	11.369
106	27	2.5	632	0.04	0.8285	3.8951	11.364
107	27	3.75	632	0.04	0.8275	3.8921	11.359
108	27	5	632	0.04	0.8303	3.8976	11.367
109	28	5.25	373	0.022	0.8303	3.8974	11.367
110	28	5.5	373	0.022	0.8301	3.8968	11.366
111	28	5.75	373	0.022	0.8299	3.8962	11.365
112	28	6	373	0.022	0.8303	3.8976	11.368

S. N	Main points	Distance from feeder (KM)	Number of Customers	Average Load, MVA	SAIFI (f/Customer. Year)	SAIDI (hr/ Customer. Year)	EENS (MWhr/ Year)
113	29	6.25	402	0.014	0.8303	3.8975	11.367
114	29	6.5	402	0.014	0.8301	3.8969	11.366
115	29	6.75	402	0.014	0.8299	3.8963	11.365
116	29	7	402	0.014	0.8303	3.8981	11.369
117	30	8.5	713	0.052	0.8293	3.8949	11.364
118	30	10	713	0.052	0.8281	3.8913	11.357
119	30	11.5	713	0.052	0.8269	3.8817	11.351
120	30	13	713	0.052	0.8303	3.8893	11.371
121	31	14.75	1049	0.05	0.8291	3.8955	11.364
122	31	16.5	1049	0.05	0.8277	3.8913	11.357
123	31	18.25	1049	0.05	0.8263	3.8871	11.350
124	31	20	1049	0.05	0.8303	3.8993	11.371
125	32	20.5	1336	0.066	0.8301	3.8985	11.370
126	32	21	1336	0.066	0.8297	3.8973	11.368
127	32	21.5	1336	0.066	0.8293	3.8961	11.366
128	32	22	1336	0.066	0.8303	3.8994	11.371
129	33	22.25	46	0.063	0.8303	3.8992	11.371
130	33	22.5	46	0.063	0.8301	3.8986	11.370
131	33	22.75	46	0.063	0.8299	3.8980	11.369
132	33	23	46	0.063	0.8303	3.8994	11.371
133	34	24.25	1512	0.072	0.8295	3.8968	11.366
134	34	25.5	1512	0.072	0.8285	3.8938	11.361
135	34	26.75	1512	0.072	0.8275	3.8908	11.356
136	34	28	1512	0.072	0.8303	3.9007	11.374
137	35	30	1437	0.05	0.8289	3.8963	11.366
138	35	32	1437	0.05	0.8273	3.8915	11.358
139	35	34	1437	0.05	0.8257	3.8867	11.349

S. N	Main points	Distance from feeder (KM)	Number of Customers	Average Load, MVA	SAIFI (f/Customer. Year)	SAIDI (hr/ Customer. Year)	EENS (MWhr/ Year)
140	35	36	1437	0.05	0.8303	3.9007	11.374
141	36	37.25	460	0.016	0.8295	3.8981	11.369
142	36	38.5	460	0.016	0.8285	3.8951	11.364
143	36	39.75	460	0.016	0.8275	3.8921	11.359
144	36	41	460	0.016	0.8303	3.9007	11.374

In MATLAB R2021a's ANN training toolbox, the Levenberg-Marquardt algorithm was employed for network training. The dataset was split into 70% for training, 15% for validation, and 15% for testing. A lower Mean Squared Error (MSE) indicated a smaller average squared difference between targets and outputs, which is desirable. A regression value close to one was ideal, indicating a strong correlation between the target and output, as demonstrated in Fig. 4.19. To enhance convergence, 20 hidden layers were employed, leading to a low MSE and a regression value close to unity, as illustrated in Fig.4.18. The overall regression value achieved after training in MATLAB was 0.93248, as illustrated in Fig.4.19. The Error Histogram in Fig.4.20 indicated that the errors between the target and output were within acceptable limits.

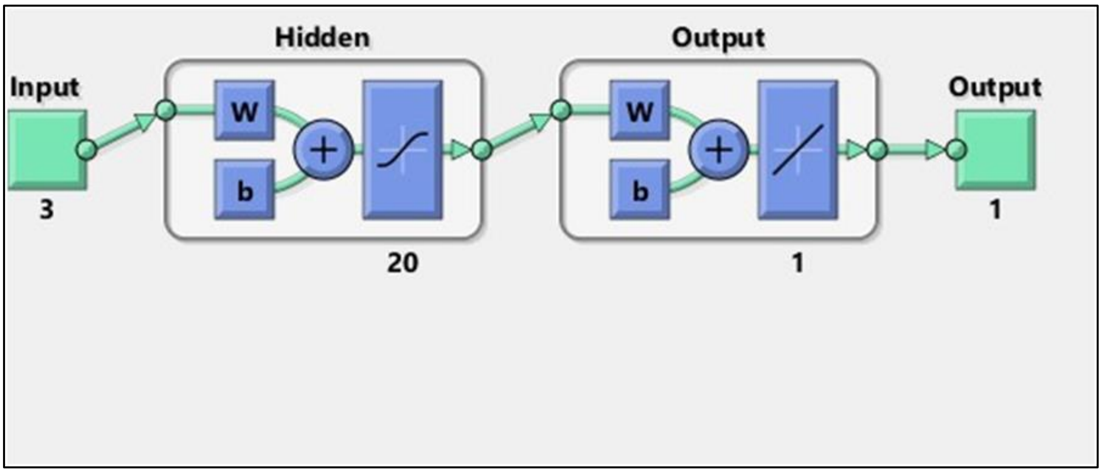

Fig. 4.18: ANN Network Diagram

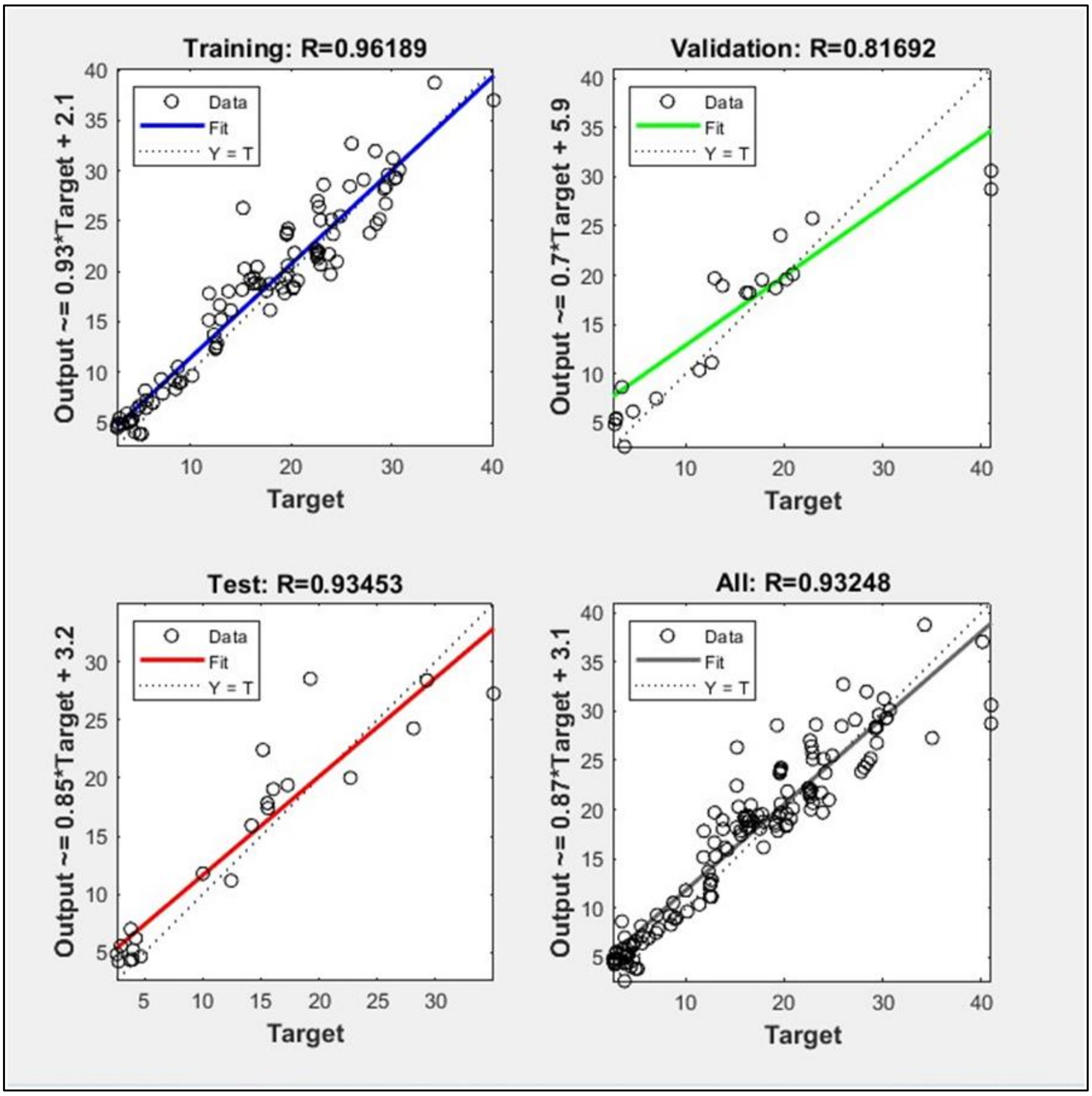

Fig. 4.19: Regression diagram for training, testing and validation

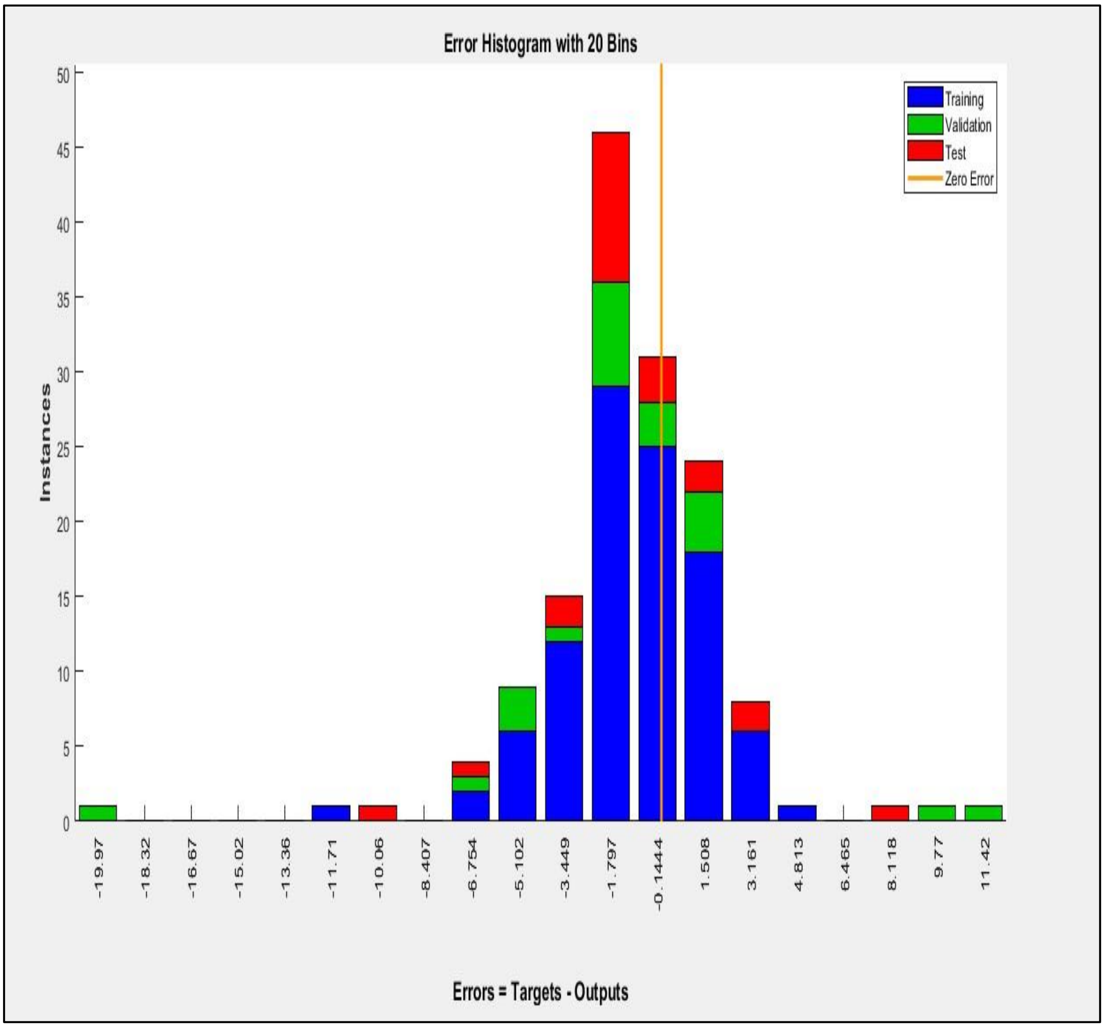

Fig. 4.20: Error Histogram curve for NN Training

Outputs for optimal locations from training on MATLAB R2021a can be denoted as Validation Location 1, 2 and 3 are near main points 4,13 and 5 at a distance of 21.84 KM, 25.48KM and 29.61KM from their feeders respectively.

4.2.3.1 DG integration in ETAP at Validation Location 1.

The Distributed Generator (DG) was installed at the optimal location identified by the training results, near Main Point 4, 21.84 km from the feeder. Fig.4.21 illustrates the DG placement. After the installation at the specified distance, a reliability test was performed using ETAP 19.0.1, and the indices were documented. As shown in Table 4.15, the reliability metrics experienced a slight decrease compared to the scenario without the DG installation, indicating a marginal improvement in reliability.

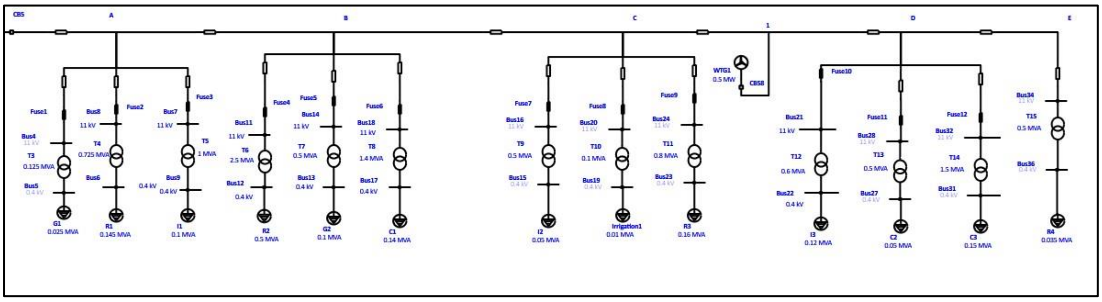

Fig. 4.21: DG integration at Validation Location 1.

Table 4.15: Summary of Reliability metrics at Validation Location 1

S. N	Reliability Metrics	Outcomes
1	SAIFI (Interruptions/ Customer/ Year)	0.7976
2	SAIDI (Hours/ Customer/Year)	3.8227
3	EENS (MWhr/ Year)	10.929
4	CAIDI (Hours/ Customer interruptions)	4.7930
5	ASAI (p.u.)	0.9996
6	ASUI (p.u.)	0.00044
7	AENS (MWhr/ Customer/ Year)	0.0003

4.2.3.2 DG Integration at Validation Location 2.

The Distributed Generator (DG) was installed near Main Point 13, 25.48 km from the feeder, based on the optimal location determined from the training results. Fig.4.22 depicts the DG placement. After the installation at the specified distance, a reliability test was performed and the metrics were documented. As shown in Table 4.16, the reliability metrics slightly increased compared to the DG placement at Validation Location 1, indicating a slight reduction in reliability.

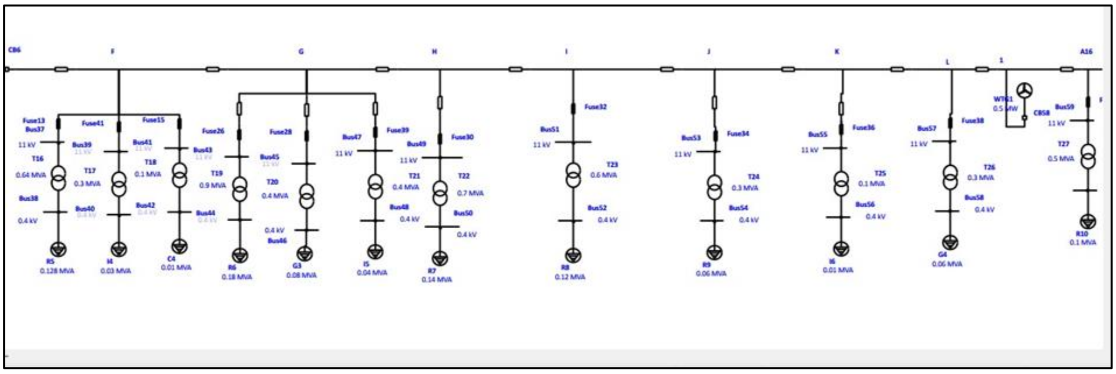

Fig. 4.22:DG Integration at Validation Location 2

Table 4.16: Summary of Reliability metrics at validation Location 2

S. N	Reliability Metrics	Outcomes
1	SAIFI (Interruptions/ Customer/Year)	0.8043
2	SAIDI (Hours/ Customer/Year)	3.8703
3	EENS (MWhr/ Year)	11.131
4	CAIDI (Hours/ Customer interruption)	4.8120
5	ASAI (pu)	0.9996
6	ASUI (pu)	0.00044
7	AENS (MWhr/ Customer. Year)	0.0003

4.2.3.3 DG integration in ETAP at Validation Location 3

The Distributed Generator (DG) was installed near Main Point 5, 29.61 km from the Besisahar feeder, based on the optimal location determined from the training results. Fig. 4.23 illustrates the DG placement. After installing at this specified distance, a reliability assessment was performed, and the metrics were documented. Table 4.18 demonstrates the most significant reduction in reliability metrics compared to previous DG placements at Validation Locations. These documented metrics validate that Location 3, as predicted by the ANN, is the optimal site for DG placement.

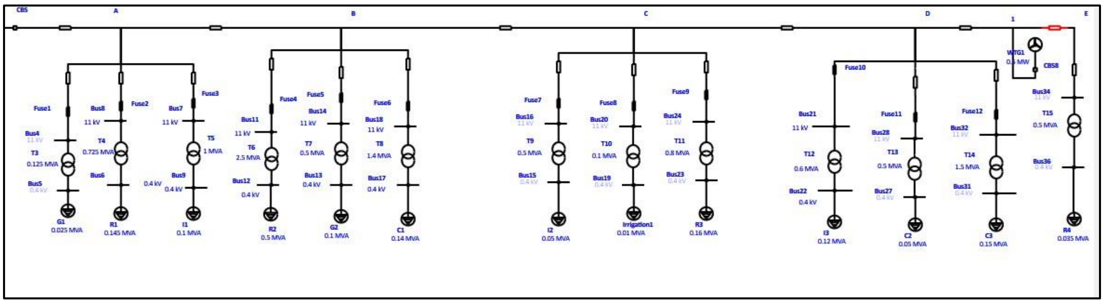

Fig. 4.23: DG at Validation Location 3.

Table 4.17: Summary of Reliability metrics at Validation Location 3

S. N	Reliability Metrics	Outcomes
1	SAIFI (Interruptions/ Customer/Year)	0.7829
2	SAIDI (hours/ Customer/Year)	3.8133
3	EENS (MWhr/ Year)	10.907
4	CAIDI (hours/ Customer interruption)	4.8710
5	ASAI (pu)	0.9996
6	ASUI (pu)	0.00044
7	AENS (MWhr/ Customer/ Year)	0.0003

Table 4.18: Summary of SAIFI, SAIDI and EENS Values at Validation Locations.

S. N	System Indices	Without DG	Validation Location 1	Validation Location 2	Validation Location 3
1	SAIFI	1.4957	0.7976	0.8043	0.7829
2	SAIDI	5.2901	3.8227	3.8703	3.8133
3	EENS	15.330	10.929	11.131	10.907

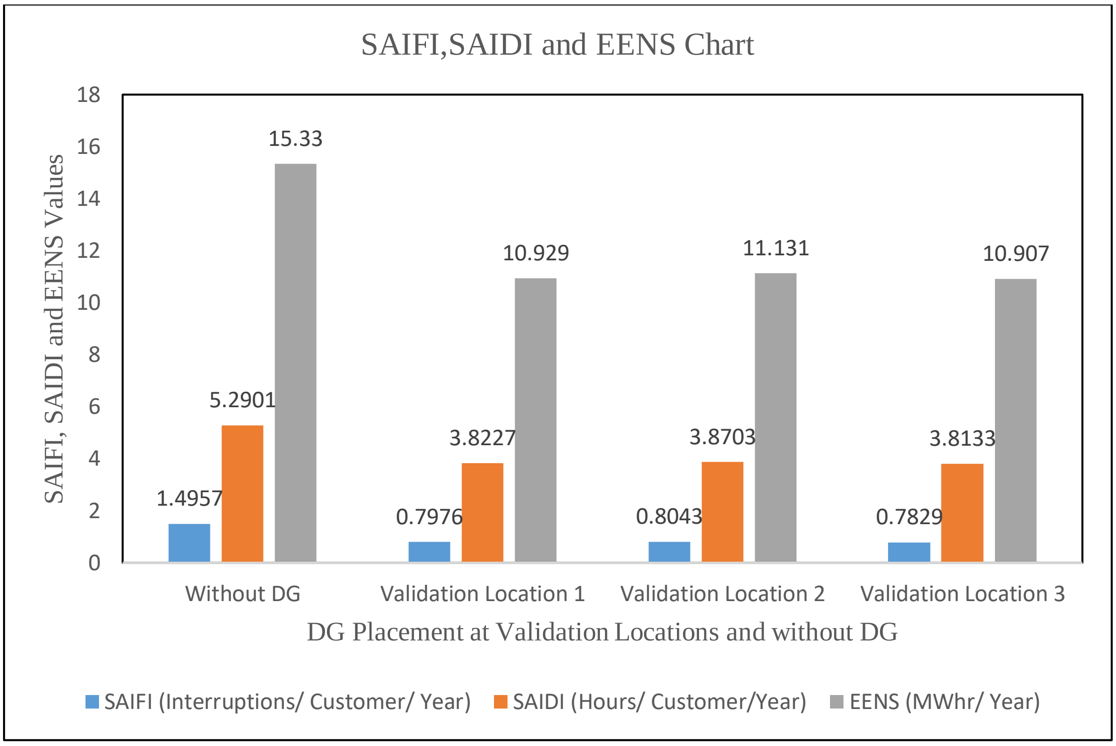

Fig. 4.24: SAIFI, SAIDI, EENS chart for DG at Validation Locations.

Optimal location for DG integration is at 29.61KM from feeder near to MP5 of feeder 1 (Besisahar feeder) which clearly shows that there is reduction in SAIFI, SAIDI and EENS values by approximately 48%, 28% and 29% respectively.

The summary of results for all three cases are mentioned below:

Base Case: During the reliability assessment performed using ETAP 19.0.1 for the RBTS bus-2 distribution system and the 33/11KV Udipur distribution system, specific indices were documented in the absence of distributed generation (DG) integration For the RBTS bus-2 distribution system, the SAIFI stood at 1.9772, SAIDI at 7.9509, and EENS at 114.089. In contrast, for the 33/11KV Udipur distribution system, the SAIFI was 1.4957, SAIDI was 5.2901, and EENS was 15.330. These values serve as the baseline reference for evaluating other cases within the study.

Case I: To determine the optimal locations for integrating distributed generation (DG) into the RBTS bus-2 and 33/11KV Udipur distribution systems, a hit-and-trial method was employed. For the RBTS bus-2 distribution system, the optimal location was identified as Main Point 14 (A). At this site, the reliability assessment conducted using

ETAP yielded the following values: SAIFI of 1.5870, SAIDI of 7.0251, and EENS of 97.619. Similarly, for the 33/11KV Udipur distribution system, the optimal location was determined to be Main Point 5 (E) of the Besisahar feeder. The recorded values for this location were a SAIFI of 0.7786 failures per year per customer, a SAIDI of 3.8085 hours per customer per year, and an EENS of 10.892 MWh per year. These outcomes indicate a decrease in SAIFI, SAIDI, and EENS, suggesting an enhancement in the reliability of the distribution systems.

Case II: To determine the optimal locations for integrating distributed generation (DG) into the RBTS bus-2 and 33/11KV Udipur distribution systems, an Artificial Neural Network (ANN) method was employed. For the RBTS bus-2 distribution system, the optimal location was identified near Main Point 14, at a distance of 2.62 km from the respective feeder. This location was validated in ETAP using an analytical approach. The reliability assessment documented the subsequent values: SAIFI was 1.5870, SAIDI was 7.0251, and EENS was 97.620. These results indicate reductions in SAIFI, SAIDI, and EENS by approximately 20%, 12%, and 15%, respectively as compared to base case.

Similarly, for the 33/11KV Udipur distribution system, the optimal location was identified near Main Point E of the Besisahar feeder, at a distance of 29.61 km from the respective feeder. This location was also validated in ETAP using an analytical approach. The reliability assessment documented the subsequent values: SAIFI was 0.7829, SAIDI was 3.8133, and EENS was 10.907. These results demonstrate reductions in SAIFI, SAIDI, and EENS by approximately 48%, 28%, and 29%, respectively in comparison to base case. Consequently, reliability was enhanced using optimal placement of DG into the distribution networks.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATION

5.1 Conclusions

This thesis demonstrates the substantial enhancements in distribution system reliability through the optimal placement of distributed generation (DG), particularly wind turbine generators, using ETAP for modeling and reliability evaluation, complemented by artificial neural networks (ANN) for optimization.

- In the RBTS BUS-2 distribution system, integrating a 1 MW wind turbine generator and optimizing its placement resulted in significant reliability improvements, with reductions of 20% in SAIFI, 12% in SAIDI, and 15% in EENS.
- For the 33/11KV Udipur Substation feeders in Lamjung District, the addition of a 0.5 MW wind turbine generator and subsequent optimization led to even more pronounced improvements, achieving reductions of 48% in SAIFI, 28% in SAIDI, and 29% in EENS.
- The application of ANN for optimizing DG placement proved to be highly effective, reducing errors inherent in the manual hit and trial approach, as well as decreasing computational complexities and processing time. This research underscores that strategically placed distributed generation can greatly enhance the reliability of long rural distribution networks.

Overall, utilizing ANN to determine optimal DG locations enhances system performance and aids in creating more resilient and efficient power distribution systems.

5.2 Future Prospects and Recommendation

Moreover, an essential continuation of this thesis could involve the comprehensive techno-economic analysis of DG integrated distribution system.

Further recommendations pertinent to this thesis include:

- For future long-term planning of distributed generation (DG), it is crucial to incorporate dynamic models, since this study was based on a static distribution network.
- To enhance reliability, advanced AI techniques could be employed to determine the optimal placement of DG units.

- The aging factor of equipment's such as transformers, conductors, breakers, fuses etc. can be taken into account for analysis.

These recommendations are essential for advancing the comprehension and practical application of the outlined research, thereby making a significant contribution to the field of Power System Engineering.

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APPENDIX A: **Customer, Configuration, Component's reliability details of RBTS Bus-2 Distribution system.**

Table-1: Details of Customers and loads.

Customer Types	Load (MVA)	Number of Customers
Residential (R)		
R1	0.535	210
R2	0.535	210
R3	0.535	200
R4	0.535	200
R5	0.535	200
R6	0.535	200
R7	0.45	200
R8	0.45	200
R9	0.45	200
Governmental(G)		
G1	0.566	1
G2	0.566	1
G3	0.566	1
G4	0.566	1
G5	0.566	1
G6	0.566	1
Commercial (C)		
C1	0.454	10
C2	0.454	10
C3	0.454	10
C4	0.454	10
C5	0.454	10
Industrial (I)		
I1	1.13	1
I2	1.3	1
Total	**12.656**	**1878**

Table-2: Feeder data for RBTS BUS -2

S. N	Length in KM	Feeder section
1	0.80	C8, C11, C16, C17, C19, C21, C22, C23, C26, C28, C33, C34, C36
2	0.75	C1, C2, C3, C5, C7, C10, C12, C13, C20, C25, C27, C30, C35
3	0.60	C4, C6, C14, C15, C18, C24, C29, C31, C32

Table-3: Data on the Reliability of Each Component.

Components	**Failure rate (Interruptions/Year)**	**Repair Time (Hour)**	**Switching Time (Hour)**
Transformers			
33/11KV, 16MVA	0.01500	15.00	1.00
11/0.4KV	0.01500	10.00	1.00
Breakers			
33.0 KV	0.00200	4.00	1.00
11.0 KV	0.00600	4.00	1.00
Busbars			
33.0 KV	0.00100	2.00	1.00
11.0 KV	0.00100	2.00	1.00
Feeders			
11.0 KV	0.6500	5.00	1.00

APPENDIX B: Details of Customers and Average loads for Udipur DS

Table-4: Details of Customers and loads.

Type of Customer	**Load (MVA)**	**Number of Customers**
Residential (R)		
R1	0.145	2191
R2	0.5	7550
R3	0.16	2417
R4	0.035	1511
R5	0.128	1461
R6	0.18	2054
R7	0.14	1598
R8	0.12	1370
R9	0.06	685
R10	0.1	1141
R11	0.04	457
R12	0.025	482
R13	0.03	579
R14	0.0375	723
R15	0.01	193
R16	0.025	482
R17	0.0375	723
R18	0.0365	704
R19	0.025	482
R20	0.0425	820
R21	0.02	575
R22	0.012	345
R23	0.014	402
R24	0.03	690
R25	0.036	1034
R26	0.046	1322
R27	0.052	1494
R28	0.05	1437

Type of Customer	Load (MVA)	Number of Customers
R29	0.016	460
Governmental (G)		
G1	0.025	40
G2	0.1	159
G3	0.08	124
G4	0.06	1
G5	0.015	70
G6	0.02	57
G7	0.01	28
Commercial (C)		
C1	0.14	95
C2	0.05	1
C3	0.15	1
C4	0.01	5
C5	0.03	1
C6	0.005	2
C7	0.02	18
C8	0.022	23
C9	0.014	15
Industrial (I)		
I1	0.1	78
I2	0.05	39
I3	0.12	47
I4	0.03	63
I5	0.04	81
I6	0.01	1
I7	0.03	25
I8	0.025	20
I9	0.02	14
I10	0.063	46
I11	0.02	18
Total	**3.412**	**36454**

APPENDIX C: Optimal location MATLAB Code and Outputs.

RBTS BUS-2 DISTRIBUTION SYSTEM

```
function [y1] = myNeuralNetworkFunction(x1)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% Auto-generated by MATLAB, 30-Mar-2024 22:06:34.
%
% [y1] = myNeuralNetworkFunction(x1) takes these arguments:
%   x = 3xQ matrix, input #1
% and returns:
%   y = 1xQ matrix, output #1
% where Q is the number of samples.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.xoffset = [1.595423617;7.080962738;97.72672136];
x1_step1.gain =
[22.3910484887223;3.33087813750672;0.154544284589022];
x1_step1.ymin = -1;

% Layer 1
b1 = [-3.3187061890191498215;-
1.4404341202066444083;2.0415377687284967934;-0.17013349793383644726;-
0.62381691263943883641;-0.44779401370718180386;-
0.65236134121481637038;0.84533624924265760026;2.9711718341139432553;3
.2672584822242334 29];
IW1_1 = [2.0231630209184010 56 -1.4799399395920040945
1.4056841920138984925;0.98480169183115717768 3.3567855090212184166 -
1.4819864628638126369;-0.80837418963042073639 3.1696504111321610608
1.1727473844944280579;1.0188476486106001762 -0.50369809746568472431
2.5511914103303885426;0.66262837869297230853 2.3566547777890187731
1.6714827314210682907;-2.9213251253904064519 -2.1720367996477425443 -
1.2958542888031769902;-1.3212741723689021001 -0.52916469435102597707
0.58817162178435311581;-0.36333424864866253889 3.5438765938210710083
-0.37176649074027146025;1.8542425376419331418 2.5713743377429310044
0.31179437786161329216;2.3352099794940368582 1.1140783697007556885 -
1.8312260618627718145];

% Layer 2
b2 = -0.52368693178667047317;
LW2_1 = [-0.34698980782958177 56 -1.2596217678425549735
1.4288884773105896553 -1.0732396154888050877 0.61908509615186280151
1.5271832030782159784 -2.0518404828641667592 0.85769319836719337 68 -
0.94444985823297600 28 -0.96265337212754331642];

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 0.727272727272727;
y1_step1.xoffset = 0.15;

% ===== SIMULATION ========

% Dimensions
```

```
Q = size(x1,2); % samples

% Input 1
xp1 = mapminmax_apply(x1,x1_step1);

% Layer 1
a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*xp1);

% Layer 2
a2 = repmat(b2,1,Q) + LW2_1*a1;

% Output 1
y1 = mapminmax_reverse(a2,y1_step1);
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings)
y = bsxfun(@minus,x,settings.xoffset);
y = bsxfun(@times,y,settings.gain);
y = bsxfun(@plus,y,settings.ymin);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
end

% Map Minimum and Maximum Output Reverse-Processing Function
function x = mapminmax_reverse(y,settings)
x = bsxfun(@minus,y,settings.ymin);
x = bsxfun(@rdivide,x,settings.gain);
x = bsxfun(@plus,x,settings.xoffset);
end
```

Distance from feeder outputs after ANN training

0.233871564000000	0.212091584000000	0.213402152000000
0.554827915000000	0.781988991000000	1.03049718700000
1.04394042500000	1.14103092000000	1.30841850600000
1.56017744300000	1.79658289600000	1.80912185100000
1.86504974100000	2.00485740900000	2.23184583700000
2.55854158200000	2.64082767300000	2.68259556700000
2.70034580700000	2.70426277000000	0.346589524000000
0.380731193000000	0.454253780000000	0.567740938000000
0.811185851000000	1.08618489500000	1.10810885600000
1.12726726600000	1.15238036800000	1.19161337900000
0.426973391000000	0.447727807000000	0.464480284000000

0.480964040000000	0.515949467000000	0.986707349000000
1.18369188400000	1.34503669600000	1.45986562200000
1.51494146600000	1.72327812800000	1.82823700400000
1.91518313800000	1.98507932000000	2.04744163900000
2.48405627400000	2.61890242400000	2.68021350300000
2.70175699100000	2.70334369500000	0.286936386000000
0.285607357000000	0.297445501000000	0.336994403000000
0.401737773000000	0.930010500000000	0.990566379000000
1.17496300900000	1.35159975300000	1.45618230100000
1.74877354700000	1.81305644900000	1.91049337500000
2.07674285600000	2.30592244600000	2.47194315000000
2.56153461400000	2.59874854400000	2.61229938700000
2.61914321700000		

33/11KV UDIPUR SUBSTATION FEEDERS

```
function [Y,Xf,Af] = myNeuralNetworkFunction(X,~,~)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% Auto-generated by MATLAB, 29-Mar-2024 22:30:19.
%
% [Y] = myNeuralNetworkFunction(X,~,~) takes these arguments:
%
%   X = 1xTS cell, 1 inputs over TS timesteps
%   Each X{1,ts} = 3xQ matrix, input #1 at timestep ts.
%
% and returns:
%   Y = 1xTS cell of 1 outputs over TS timesteps.
%   Each Y{1,ts} = 1xQ matrix, output #1 at timestep ts.
%
% where Q is number of samples (or series) and TS is the number of
timesteps.

%#ok<*RPMT0>

% ===== NEURAL NETWORK CONSTANTS =====

% Input 1
x1_step1.xoffset = [0.25;1;0.005];
x1_step1.gain                                                    =
[0.049079754601227;0.000256311674996796;2.72108843537415];
x1_step1.ymin = -1;

% Layer 1
```

```
b1                                 =                                 [-
3.7615372927313717177;3.4481692451755501239;3.5248835239724196633;-
2.7250708998769734848;-1.7990547134517524963;1.4416392117868590539;-
2.6488568665545382252;2.1206416244064785204;1.0110123617590607292;-
0.97537274171460697225;1.2959065435405949795;-
1.2165588988621895972;1.0429329189394478394;0.25460523559120118442;-
1.3805029843758389596;1.5986913959966166932;2.5191580033518357062;-
0.28799590652714790462;3.2971154020615598412;-5.6257739750133231027];
IW1_1      =      [2.1327347452712168696      -2.1679543391361328908
2.3328494851749996819;-0.31121588895586654866  -1.1457525421488685691
-3.5483428292607892551;-0.5831795093077242198 1.4249533344988003503 -
3.9326044507144470863;-0.54905000922254348985  -0.37084088180499541476
-1.2050998004298465460.30995608726384898945 -3.2125200835291027879 -
1.7567611715021480556;-4.7318013228455146901  -0.35430185190538415752
0.35212482328477184845;2.7446782365111221935   -1.5764562940175907979
3.5744742300958320946;-2.3076697400923542602  0.038247440863451609427
1.9376195723594671350;-1.5636174439510308609  3.3632957712506157399  -
0.10537098677327821905;2.9301110811986212923  1.9621314813645960307  -
0.60013859903224031633;2.4266726422145601383    2.6992760745152839519
1.0636990901763925255;-1.1196749178045390938 -2.3578893749241629507 -
3.2266090025160472088;0.48937256212671786937   -3.5713549607332581992
0.79371742977221371174;2.4192974018730022401     2.374053806586953641
2.4898053261416288606;-3.3127507851278035211  1.471235139709393458  -
0.49189192386002467128;2.1841169361676135985  3.4954254341385273541  -
1.1497542144896015781;1.6396482576824229493 -3.2633547932811448611  -
1.0307819048956201602;-3.0027188727092770648  2.3345339954374826341  -
2.5888675870104256305;0.7298834535481294461    -2.8501236411271313465
2.4477227850753577876;-4.4107676085643587882 -2.6582019655376885048 -
1.465498300513949248];

% Layer 2
b2 = -0.4624982124486805013;
LW2_1      =      [-0.38131109289028841669      0.13786127368570721963
0.21194461139647335912 1.1417781036198058064 1.0085664240347436138 -
0.23851600502220074444 -0.19947379692478961477 -0.30336703111449703218
0.88565266290818889239  -1.1474686194117691418  1.5723728701195442969
1.1798033447636684379 0.65839208961173800727 1.3989431888804713111 -
0.21245806681098369784 -0.36839347582947185034 0.45135176436495422214
-0.11362934331400871557             -0.69093446369005973029            -
0.49485218443186751447];

% Output 1
y1_step1.ymin = -1;
y1_step1.gain = 0.0521696742624346;
y1_step1.xoffset = 2.647104757;

% ===== SIMULATION ========

% Format Input Arguments
isCellX = iscell(X);
if ~isCellX
    X = {X};
end

% Dimensions
TS = size(X,2); % timesteps
if ~isempty(X)
    Q = size(X{1},2); % samples/series
else
```

```
    Q = 0;
end

% Allocate Outputs
Y = cell(1,TS);

% Time loop
for ts=1:TS

    % Input 1
    Xp1 = mapminmax_apply(X{1,ts},x1_step1);

    % Layer 1
    a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*Xp1);

    % Layer 2
    a2 = repmat(b2,1,Q) + LW2_1*a1;

    % Output 1
    Y{1,ts} = mapminmax_reverse(a2,y1_step1);
end

% Final Delay States
Xf = cell(1,0);
Af = cell(2,0);

% Format Output Arguments
if ~isCellX
    Y = cell2mat(Y);
end
end

% ===== MODULE FUNCTIONS ========

% Map Minimum and Maximum Input Processing Function
function y = mapminmax_apply(x,settings)
y = bsxfun(@minus,x,settings.xoffset);
y = bsxfun(@times,y,settings.gain);
y = bsxfun(@plus,y,settings.ymin);
end

% Sigmoid Symmetric Transfer Function
function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1;
end

% Map Minimum and Maximum Output Reverse-Processing Function
function x = mapminmax_reverse(y,settings)
x = bsxfun(@minus,y,settings.ymin);
x = bsxfun(@rdivide,x,settings.gain);
x = bsxfun(@plus,x,settings.xoffset);
end
```

Distance from feeder outputs after ANN training

2.61732703300000	4.95462163100000	7.03180086900000
8.65037938300000	8.33271704200000	7.49585122000000
6.24258572100000	4.42137600700000	15.2437593100000
16.1645114000000	17.8406846100000	20.4536108800000
19.0873995800000	19.6950632700000	20.5755328000000
21.8424727700000	23.7169322400000	26.7433946600000
29.6096581000000	31.9619095100000	12.3164249000000
12.3279705400000	12.4997781800000	12.8570505400000
3.84755375500000	4.68382133300000	5.35128859600000
5.87082389800000	18.0549810000000	18.9347816800000
19.6932003500000	20.2797196700000	18.7879476500000
19.2837344300000	19.5861720600000	19.7076512600000
16.1508328300000	17.4088143900000	18.2369915600000
18.7720033500000	20.0152028300000	20.6834869400000
21.2933344600000	21.8513692800000	21.5505210200000
21.7648295900000	21.9727694100000	22.1751996900000
19.3947083900000	21.7193632000000	25.4849795600000
30.0964202800000	29.2435389700000	29.3327888800000
29.1133363100000	28.6225949300000	28.4597766200000
28.3949419800000	28.3895158800000	28.5331676400000
4.87814712400000	4.66292461100000	4.45912861700000
4.26699167200000	4.80993338900000	4.37862925300000
4.05944840600000	3.85362584100000	5.31138765800000
5.23614974000000	5.18014911700000	5.14395521100000
6.18475328400000	6.30981856400000	6.65001276100000
7.21496912300000	9.01981666000000	9.65573646300000
10.3726392500000	11.1528123900000	8.17334573700000
9.30878236400000	10.5290143100000	11.7968330400000
15.1653402100000	16.6560519800000	17.8497984600000
18.7655300500000	18.8579106800000	19.0500838000000
19.2225430800000	19.4018964200000	19.5370794700000

20.1113754700000	20.9717481000000	22.1711562100000
23.8174916100000	24.2669750900000	24.7294152000000
25.1929985100000	25.1084264100000	25.7731392100000
26.4115147600000	27.0112376600000	9.18952508100000
7.88835253800000	6.94328436600000	6.44649240900000
4.89161141800000	4.88023002200000	4.88722635200000
4.91297757900000	5.36812316400000	5.41916263600000
5.49026499100000	5.58185608400000	8.92422154700000
11.1926556700000	13.7317687600000	15.9329092400000
18.4608431500000	18.3941762700000	18.1816457200000
18.2251702100000	17.8147231600000	18.0232753700000
18.3167052600000	18.6999483500000	23.6678355500000
23.8542124400000	24.0439285100000	24.2375991500000
22.4225759200000	25.1479531900000	28.2024626700000
31.2405860000000	32.7059317600000	35.1895044100000
37.0146712000000	38.7477081700000	26.3080428000000
27.2592814000000	28.7274634200000	30.5973212400000

APPENDIX D: Paper Acceptance Notification and Conference Paper.

Gmail **bibas acharya <bibas.acharya999@gmail.com>**

[IOEGC15] Editor Decision

IOEGC15 Publication Committee <conference-noreply@ioe.edu.np> Tue, Jun 11, 2024 at 10:31 PM
To: BIBAS RAJ ACHARYA <bibas.acharya999@gmail.com>, Nava Raj Karki <nrkarki@ioe.edu.np>, Shahabuddin Khan <sk@pcampus.edu.np>

BIBAS RAJ ACHARYA; Nava Raj Karki, Shahabuddin Khan:

We have reached a decision regarding your submission to 15th IOE Graduate Conference, "Reliability Enhancement of Electric Distribution Network Using Optimal Placement of Distributed Generation. A Case Study of 33/11KV Udipur Distribution Substation feeders, Lamjung".

Our decision is to: **Accept Submission**

____

[*This email is auto-generated from 15th IOE Graduate Conference web portal*]

IOE Graduate Conference
[Placeholder for Publication Information]

Reliability Enhancement of Electric Distribution Network Using Optimal Placement of Distributed Generation: A Case Study of 33/11KV Udipur Distribution Substation Feeders, Lamjung

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Abstract

Reliability can be considered as the capability of system to survive. Currently, consumers are demanding reliable and cheaper power supply with reduced interruption duration. It's widely acknowledged that nearly 90% of electricity interruptions generates from faults within the electric distribution system. Integration of Distributed Generations (DG) into distribution network can significantly enhance its reliability in several ways such as redundancy, reduced transmission losses, voltage support, load sharing, resilience to disasters, peak shaving, islanded operation, flexibility and modularity. Artificial Neural Network (ANN) is used to obtain the optimal location of DG based on the minimum values of reliability indices SAIFI, SAIDI and EENS for which inputs are taken as average load, distance from the feeder, number of customers connected. Electrical Transient Analyzer Program (ETAP) is a software tool widely used for the design, analysis, and operation of power systems. When it comes to reliability evaluation of distribution networks, ETAP offers several advantages such as comprehensive analysis, reliability indices calculation, fault analysis and simulation, load flow analysis, optimization and planning, integration with other modules etc. Reliability was enhanced in the Udipur substation feeder following the placement of Distributed Generation (DG) as determined by Artificial Neural Networks (ANN). This improvement is evident in the system reliability indices, with a decrease in SAIFI, SAIDI by approximately 48% and 28% respectively. Furthermore, there was an improvement in terms of Cost of Reliability Indices, with a reduction in EENS by approximately 29%. The radial distribution network of the Roy Billiton Test System (RBTS) connected at bus-2 and 33/11KV Udipur Substation Outgoing feeders is used as a case study, where different types of loads such as Residential, Commercial, Industrial and Governmental & Institutional are connected.

Keywords

Reliability, Distribution System, Distributed Generation (DG) Artificial Neural Network (ANN), SAIFI, SAIDI, EENS, ETAP.

1. Introduction

The Reliability evaluation of a distribution system primarily focuses on how well it performs at the customer's end, where electricity demand is met. Key indicators used for predicting this reliability include the average failure rate at load points, the typical duration of outages experienced by customers, and the yearly cumulative outage time, or unavailability [1]. These indices are crucial for understanding reliability from both the customer's perspective and the utility's viewpoint. However, they don't offer a comprehensive overview of system performance. To achieve a more holistic understanding, additional indices can be derived from these basic indicators, considering the number of customers or loads connected at each load point in the system. Many of these additional indices are weighted averages of the fundamental load point indices. Among the most prevalent system-level indices are SAIFI, SAIDI, CAIFI, CAIDI, ASAI, ASUI, ENS, and AENS. Utilities often calculate these indices based on historical interruption data, offering valuable insights into past system performance [1]. Distributed Generation (DG) refers to electric-power

Pages: 1 – 8

generating units installed in close proximity to load centers. This strategic placement of DG units allows for the bypassing of electric power transmission lines, effectively bringing power generation closer to the areas of demand. In contrast, a conventional electric supply system operates on a centralized model, consisting of generating units, transmission lines, and a distribution network. However, this conventional power system exhibits poor reliability owing to its complex configuration. A fault occurring at a single location within the system can trigger the entire feeder to trip, resulting in disruption to all consumers connected to that feeder [2]. An Artificial Neural Network (ANN) is an advanced machine learning technique inspired by the human capacity for imitation or learning through observation and replication [3]. Among the many types of artificial neural network (ANN) methodologies, the backpropagation (BP) learning algorithm has emerged as highly favored in engineering applications. This type of network typically comprises three layers: an input layer, a hidden layer, and an output layer. To effectively train and evaluate neural networks, datasets containing input patterns and corresponding targets are essential. When developing an ANN model, the available dataset is typically split into two subsets. The majority portion (around 70-80% of the data) is used for training the network, while the remainder is reserved to assess the network's ability to generalize beyond the training data [3]. Understanding different aspects of reliability is crucial when assessing the availability of power supply within a distribution system. One key reliability measure of significance is the failure rate of the distribution system. This index provides fundamental insight into the system's reliability and its ability to consistently deliver electricity without interruptions or breakdowns [4]. The training function of the feed-forward backpropagation network utilizes the Bayesian Regularization algorithm to update weight and bias values. This methodology is particularly suitable for training Neural Networks (NN), employing the mean squared error (MSE) as a performance metric. The backpropagation learning rule, integral to this process, is a continuous stochastic optimization technique aimed at minimizing the MSE between the actual and desired output. [5]. The Levenberg-Marquardt algorithm (LMA), is adopted for training the network. This algorithm takes less time as training process automatically stops when generalizations stop improving as indicated by increase in Mean Square Error of validation samples. To maximize this improvement, placing DG units far from feeder rather than placing it close to load center [6]. The Udipur Substation, situated in Lamjung district of Nepal, is connected to a distribution network comprising four radial feeders: the Besisahar feeder, Bhoteodar feeder, Okhari feeder, and Nayagaun feeder. These feeders serve a total of 36,454 customers of various types. The combined radial length of these feeders extends to 129.5 kilometers, with an additional 112 kilometers comprising the lateral lengths. The radial sections utilize Rabbit conductors with a 50 mm² cross-sectional area, while the lateral sections use Weasel conductors with a 30 mm² cross-sectional area. Data on feeder tripping frequency and outage duration were collected over the year from 2079-07-01 to 2080-06-30. This data was used to calculate failure rates and Mean Time to Repair (MTTR) for each of the four feeders, and these data were subsequently integrated into the ETAP 19.0.1 software for a reliability assessment. The average load handled by the Udipur Substation is 3.412 MW, with the Besisahar feeder bearing the highest load among the four feeders.

2. Reliability Indices

2.1 Load Point Reliability Indices

Failure Rate (λ): Failure/ year/Km[5]

$$\lambda = \sum_{i=1}^{n} \lambda_i \tag{1}$$

Annual Outage Duration(U): Hours/year.[5]

$$U = \sum_{i=1}^{n} r_i * \lambda_i \tag{2}$$

Average Outage Duration (r): Hours/failure[5]

$$r = \frac{\sum_{i=1}^{n} r_i * \lambda_i}{\sum_{i=1}^{n} \lambda_i} = \frac{U}{\lambda} \tag{3}$$

2.2 System Reliability Indices

System Average Interruption Frequency Index (SAIFI): Failure/ year.Customer
SAIFI represents the average number of interruptions experienced by each utility customer within a specified analysis period. Typically, SAIFI is

measured over the span of a year.[5]

$$SAIFI = \frac{\sum_{i=1}^{n} N_i * \lambda_i}{\sum_{i=1}^{n} N_i} \quad (4)$$

System Average Interruption Duration Index (SAIDI): Hours/ year.Customer
SAIDI represents the average duration of all interruptions experienced by each utility customer over the analysis period.[5]

$$SAIDI = \frac{\sum_{i=1}^{n} N_i * U_i}{\sum_{i=1}^{n} N_i} \quad (5)$$

Customer Average Interruption Duration Index (CAIDI): Hours/ Failure
It is the average time needed to restore service to the average customer per sustained interruption.[5]

$$CAIDI = \frac{SAIDI}{SAIFI} \quad (6)$$

Average Service Availability Index (ASAI):
ASAI is the ratio of the total number of customer hours that service was available during a given time period to the total customer hours demanded. It is normally expressed in percentage.[5]

$$ASAI = 1 - \frac{SAIDI}{8760} \quad (7)$$

2.3 Cost Worth Reliability Indices

Expected Energy Not Supplied (EENS): MWhr /year
EENS Specifies the average energy that is not supplied to the customer in the predefined time.[5]

$$EENS = \sum_{i=1}^{n} U_i * L_i \quad (8)$$

Expected Cost of Interruption (ECOST):$/year
It may be defined as the cost of EENS. It is calculated as the product of EENS and its cost per KWhr.[5]

$$ECOST = \sum_{i=1}^{n} \lambda_i * C_i * L_i \quad (9)$$

3. Methodology

In this research study, an evaluation of the reliability of contemporary distribution networks was carried out by incorporating a DG source, simulated using the Electrical Transients and Analysis Program (ETAP), followed by an analysis of its effects. Various experiments employing a hit and trial approach were performed to determine the best placement within the distribution system. After that, an ANN technique was used to find the optimal location for the DG. In this research, the focus is on utilizing the feedforward backpropagation Neural Network (NN) among various ANN techniques, which is particularly effective for addressing fitting problems. This NN architecture comprises three layers: input, hidden, and output layers. To train and validate the network, input data patterns along with corresponding output data are essential. During the development phase of the ANN model, the available data is divided into three sets. Approximately 70% of the data is allocated for training the network, 15% is reserved for validation purposes, and the remaining 15% is used specifically for testing the performance of the NN. In this study, the research involves employing the tan-sigmoid transfer function within both the hidden and output layers of the neural network. Specifically, for RBTS Bus-2 and the 33/11KV Udaipur Substation feeders, the hidden layers consist of 10 and 20 neurons respectively, while there is 1 neuron in the output layer and 3 neurons in the input layer. The feedforward backpropagation network is trained using the Levenberg-Marquardt algorithm, which iteratively updates the weights and biases to optimize network performance. The primary objective is to minimize the Mean Squared Error (MSE) between the actual and desired output values. The MSE serves as a continuous stochastic optimization metric, guiding the network towards more accurate predictions and improved performance.

$$MSE = \frac{1}{n} \sum_{n}^{i=1} (O_i - O_k)^2 \quad (10)$$

Where, O_i is the output obtained of the i^{th} pattern, O_k is the desired output of the the k^{th} pattern and n is the count of patterns. The methodology was applied and validated using RBTS bus 2 and 33/11KV Udipur substation feeders to confirm our results. A flowchart of the proposed approach is illustrated in Figure 1.

4. Case Studies

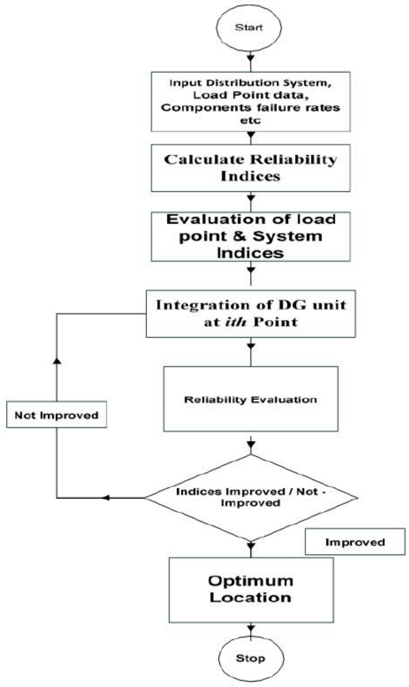

Figure 1: Overall System Methodology

4.1 RBTS Bus-2 Distribution system

The single line diagram of IEEE RBTS Bus-2 (33/11KV) main feeder is as shown in figure.2. This diagram consists of four numbers of sub feeders and all combined have 22 load points, 14 main points, 22 transformers of 2 MVA, 11/0.4KV distribution transformers, circuit breakers and cables. The system has a total of 1878 customers connected to it, with an average load of 12.656 MVA are detailed in Table 1. These customers belong to various categories, including Residential, Governmental and Institutional, Commercial, and Industrial, and they are distributed across different feeders within the system. Reliability information for critical components like Power Transformers, Breakers, Cables, Distribution Transformers, and Busbars, including failure rates, repair times, and switching times, is detailed in Table 2 . Additionally, Table 3 provides the lengths of cable sections utilized within the system.

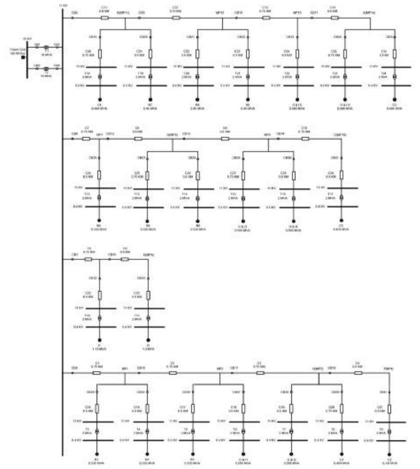

Figure 2: RBTS Bus-2 Distribution System

4.2 33/11KV Udipur Substation feeders

The single line diagram of 33/11KV Udipur Substation feeders is as shown in Figure 3. This diagram consists of four numbers of sub feeders and all combined have 57 load points, 36 main points, 57 numbers of different ratings lumped transformers of 11/0.4KV distribution transformers, circuit breakers and fuses. 4 presents the tripping frequency, repair time, and operational hours for four feeders, along with the calculated failure rate and Mean Time to Repair (MTTR). These metrics provide insights into the reliability and maintenance efficiency of the feeders. Meanwhile, Table 5 displays the number of customers, average load, radial length, lateral length, and total length for each feeder. These parameters are crucial for assessing the network's capacity, distribution, and geographical coverage.

5. Results and Discussion

5.1 RBTS bus-2 distribution system

5.1.1 Reliability analysis with no DG Connected

A reliability analysis was conducted in ETAP 19.0.1 for RBTS bus-2, focusing on modeling without Distributed Generation (DG) connectivity. The analysis incorporated the provided failure rates and Mean Time To Repair (MTTR) data for the equipment, as well as the number of customers and

Table 1: Type, Number of Customers and average loads of load points

Type of Customer	Load (MVA)	Number of Customers
Residential		
Residential 1	0.535	210
Residential 2	0.535	210
Residential 3	0.535	200
Residential 4	0.535	200
Residential 5	0.535	200
Residential 6	0.535	200
Residential 7	0.45	200
Residential 8	0.45	200
Residential 9	0.45	200
Government and Institution (G & I)		
G & I 1	0.566	1
G & I 2	0.566	1
G & I 3	0.566	1
G & I 4	0.566	1
G & I 5	0.566	1
G & I 6	0.566	1
Commercial		
Commercial 1	0.454	10
Commercial 2	0.454	10
Commercial 3	0.454	10
Commercial 4	0.454	10
Commercial 5	0.454	10
Industrial		
Industrial 1	1.13	1
Industrial 2	1.3	1
Total	12.656	1878

average load. The results of this analysis are summarized in Table 6. This modeling approach allows for an evaluation of the reliability and performance of RBTS bus-2 under normal operating conditions without the influence of DG systems.

5.1.2 Injecting DG at different locations to find the optimal location

To determine the optimal location for injecting Distributed Generation (DG), a wind turbine with a capacity of 1 MW is utilized. This wind turbine, modeled as a Type-III DG source in generic mode within ETAP, has a failure rate of 0.03 failures per year and a repair time of 50 hours. It can inject both real and reactive power into the system. The process involves a hit and trial method, where the wind turbine is injected at various main points to identify the most suitable location. Table 7 presents the values for reliability indices such as SAIFI, SAIDI, and EENS. According to the results in Table 7, the optimal location for injecting the DG is determined to be point A, specifically Main Point 14 (MP14) having minimum values of SAIFI, SAIDI, and EENS. In

Table 2: Reliability data of each component

Components	Failure Rate (F/Year)	Repair Time (Hour)	Switching Time (Hour)
Transformers			
33/11KV, 16MVA	0.015	15	1
11/0.4KV (LT)	0.015	10	1
Breakers			
33.0 KV	0.002	4	1
11.0 KV	0.006	4	1
Busbars			
33.0 KV	0.001	2	1
11.0 KV	0.001	2	1
Feeders			
11.0 KV	0.65	5	1

Table 3: Feeder Section

S. N	Length in KM	Feeder section
1	0.8	C8, C11, C16, C17, C19, C21, C22, C23, C26, C28, C33, C34, C36
2	0.75	C1, C2, C3, C5, C7, C10, C12, C13, C20, C25, C27, C30, C35
3	0.6	C4, C6, C14, C15, C18, C24, C29, C31, C32

Figure 4, SAIFI values at various locations are depicted with DG connections, illustrating that the minimum SAIFI values occur at location A.

5.1.3 ANN to find the optimal location of DG

By implementing Distributed Generation (DG) at different distances ranging from 20% to 100% for 14 main points along their respective feeders, we acquired 70 numbers of corresponding data for SAIFI, SAIDI and EENS from ETAP simulation outputs for training purpose. Levenberg- Marquardt algorithm is

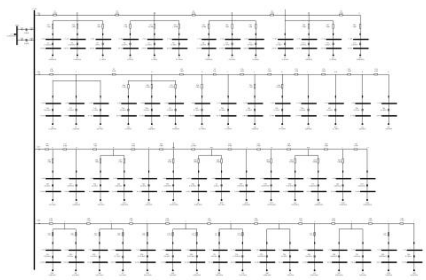

Figure 3: 33/11KV Udipur Distribution feeders.

Table 4: Feeder tripping frequency and Outage duration (2079-07-01 to 2080-06-30)

S.N	Name of Feeder	No of tripping	Repair time	Operation hour	Failure rate (No of tripping /Operation Hour)	Mean time to Repair
1	Besishahar	57	38.966	8721.03	0.0065	0.68
2	Bhoteodar	69	52.183	8707.82	0.0079	0.76
3	Okhari	88	98.55	8661.45	0.0102	1.12
4	Nayagaun	100	146.633	8613.37	0.0116	1.47

Table 5: Feeder's length and Number of Customers

S.N	Name of Feeder	Number of Customers	Average Load (MVA)	Radial Length (KM)	Lateral Length (KM)	Total Length (KM)
1	Besishahar	14131	1.590	24	22.5	47
2	Bhoteodar	9041	1.000	36	13.5	50
3	Okhari	5324	0.377	28.5	32.5	61
4	Nayagaun	7958	0.445	41	43.5	85
Total		36454	3.412	129.5	112	241.5

adopted for training the network. This algorithm takes less time as training process automatically stops when generalizations stop improving as indicated by increase in Mean Square Error of validation samples. Out of total training datasets, 70% have been used for training purpose, 15% for validation and remaining 15% for testing purpose. Lower value of MSE signifies that average squared difference between targets and outputs are lower which is preferred. Regression value close to unity is preferred which signifies there is close relationship between target and output. Number of hidden layers are taken so as to have better convergence, lower value of MSE and Regression value close to unity. Training set best locations have been validated in ETAP software to identify optimal location for DG integration so as to have minimum values of SAIFI, SAIDI, EENS. Outputs for optimal locations from training on MATLAB R2021a can be denoted as Location 1, Location 2 and Location 3 are near Main points 7, 8 and 14 at a distance of 0.48 KM, 1.51 KM and 2.62 KM from their feeders respectively. These locations are validated with analytic approach in ETAP as shown in Table 11. Figure 7 shows the Regression

Table 6: Reliability Indices without DG

S. N	System Indices	Results
1	SAIFI (f/ Customer. Year)	1.9772
2	SAIDI (hr./ Customer. Year)	7.9509
3	EENS (MWh/ Year)	114.089
4	CAIDI (Hr./ Cust interruption)	4.021
5	ASAI (pu)	0.9991
6	ASUI (pu)	0.00091
7	AENS (MWhr/ Customer. Year)	0.0608

Table 7: SAIFI, SAIDI and EENS values with DG at different locations

DG injection points	SAIFI (failure/Customer.year)	SAIDI (hr/Customer.year)	EENS (MWhr/year)
A	1.5870	7.0251	97.619
B	1.7134	7.6499	110.575
C	1.5962	7.0692	98.991
D	1.6031	7.1022	104.103
E	1.7214	7.6810	107.470
F	1.6429	7.3025	99.455
G	1.6456	7.316	100.596

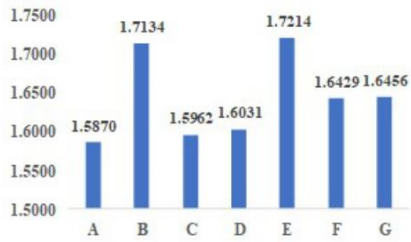

Figure 4: SAIFI values at different locations.

analysis for testing of ANN model which clearly shows the Regression value close to unity means there is close relationship between target and output.

Table 8: Summary of SAIFI, SAIDI and EENS values at validation locations

S. N	Reliability Indices	Validation Location 1	Validation Location 2	Validation Location 3
1	SAIFI (f/ Customer. Year)	1.7138	1.6033	1.587
2	SAIDI (hr./ Customer. Year)	7.6508	7.1024	7.0251
3	EENS (MWh/ Year)	110.596	104.105	97.62

5.2 33/11KV Udipur Substation Distribution System.

5.2.1 Reliability analysis with no DG Connected

The Udiipur distribution system is modeled in ETAP 19.0.1 using data sourced from the log sheet of the Lamjung Distribution Centre operated by the Nepal Electricity Authority (NEA). This data encompasses tripping frequency, interruption duration, average load, information on types of customers, the number of customers connected to different load points, and the sizes of transformers deployed within the Lamjung Distribution Centre. Subsequent to conducting a reliability assessment within ETAP, the resulting reliability indices are compiled and displayed in Table 9.

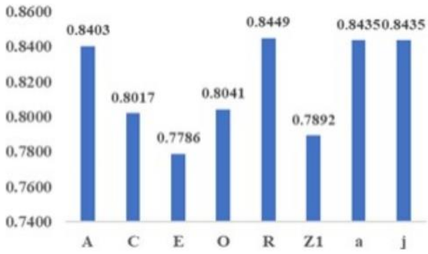

Figure 5: SAIFI Values with DG at different locations

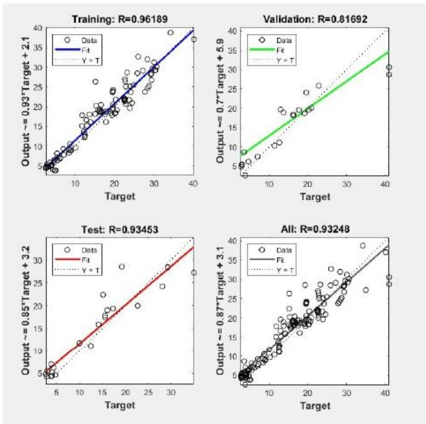

Figure 6: Regression Analysis for testing of ANN model

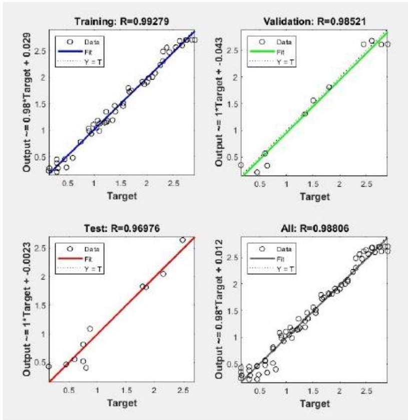

Figure 7: Regression analysis for testing of ANN model

Table 9: Reliability Indices without DG of Udipur Distribution System

S.N	System Indices	Results
1	SAIFI (f/ Customer. Year)	1.4957
2	SAIDI (hr/ Customer. Year)	5.2901
3	EENS (MWh/ Year)	15.33
4	CAIDI (Hr/ Cust interruption)	3.537
5	ASAI (pu)	0.9994
6	ASUI (pu)	0.0006
7	AENS (MWhr/ Customer.Year)	0.0004

5.2.2 Injecting DG at different locations to find the optimal location.

To determine the optimal location for injecting Distributed Generation (DG), a wind turbine with a capacity of 0.5 MW is utilized. This wind turbine, modeled as a Type-III DG source in generic mode within ETAP, has a failure rate of 0.03 failures per year and a repair time of 50 hours. It can inject both real and reactive power into the system. The process involves a hit and trial method, where the wind turbine is injected at various main points to identify the most suitable location. Table 10 presents the values for reliability indices such as SAIFI, SAIDI, and EENS. According to the results in Table 10, the optimal location for injecting the DG is determined to be point E, specifically Main Point 5 (MP5) having minimum values of SAIFI, SAIDI, and EENS. The SAIFI values at different locations after injecting DG has been shown in the graph in Figure 5.

5.2.3 ANN to find the optimal location of DG

By implementing Distributed Generation (DG) at different distances ranging from 25% to 100% for 36 main points along their respective feeders, we acquired corresponding data for SAIFI, SAIDI and EENS from ETAP simulation outputs. It's worth noting that the number of customers and average load were kept constant, while adjustments were made to the distances of the main points from the feeders, ensuring a constant total radial length for each feeder. Outputs for optimal locations from training on MATLAB R2021a can be denoted as Location 1, Location 2 and Location 3 are near Main points 4, 5 and 13 at a distance of 21.84 KM, 29.61 KM and 25.48 KM from their feeders respectively. Number of hidden layers have been selected so as to have minimum value of MSE and Regression value close to

Table 10: Reliability Indices with DG at different locations

DG injection points	SAIFI (failure/Customer. Year)	SAIDI (hr./Customer. Year)	EENS (MWhr/Year)
A	0.8403	3.8505	11.066
C	0.8017	3.8243	10.949
E	0.7786	3.8085	10.892
O	0.8041	3.8698	11.129
R	0.8449	3.9347	11.427
Z1	0.7892	3.8726	11.318
a	0.8435	3.9066	11.399
j	0.8435	3.9097	11.405

unity. Figure 6 shows the Regression diagram for training , validation and testing process which clearly shows regression value close to unity showing closer relationship between target and output. DG has been placed on ETAP simulation at validation locations to validate the results so as to obtain values for SAIFI, SAIDI and EENS. Table clearly shows that minimum values of SAIFI, SAIDI and EENS is obtaine at validation location 2.

Table 11: Summary of SAIFI, SAIDI and EENS at Validation Locations

S. N	Reliability Indices	Validation Location 1	Validation Location 2	Validation Location 3
1	SAIFI (f/ Customer. Year)	0.7976	0.7829	0.8043
2	SAIDI (hr./ Customer. Year)	3.8227	3.8133	3.8703
3	EENS (MWh/ Year)	10.929	10.907	11.131

6. Conclusion

In RBTS Bus-2 Distribution System, there was reduction in values of SAIFI, SAIDI and EENS by 20%, 12% and 15% respectively. In 33/11KV Udipur Substation feeders, there was reduction in values of SAIFI, SAIDI and EENS by 48%,28% and 29% respectively. Implementing ANN can reduce the errors caused by human hit and trial methods and also lead to reductions in computational complexities and processing time. Distributed Generation can significantly improve distribution system reliability on long rural distribution network if it will be installed at proper location.

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APPENDIX E: Originality Report

Reliability Enhancement of Electric Distribution Network Using Optimal Placement of Distributed Generation: A Case Study of the 33/11kV Udipur Substation Distribution feeders, Lamjung

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