Proceedings of 15th IOE Graduate Conference
Peer Reviewed
Year: 2024 Month: May Volume: 15
ISSN: 2350-8914 (Online), 2350-8906 (Print)

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 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]

$$\text{SAIFI} = \frac{\sum_{i=1}^{n} N_i * \lambda_i}{\sum_{i=1}^{n} N_i} \tag{4}$$

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]

$$\text{SAIDI} = \frac{\sum_{i=1}^{n} N_i * U_i}{\sum_{i=1}^{n} N_i} \tag{5}$$

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]

$$\text{CAIDI} = \frac{\text{SAIDI}}{\text{SAIFI}} \tag{6}$$

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]

$$\text{ASAI} = 1 - \frac{\text{SAIDI}}{8760} \tag{7}$$

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]

$$\text{EENS} = \sum_{i=1}^{n} U_i * L_i \tag{8}$$

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]

$$\text{ECOST} = \sum_{i=1}^{n} \lambda_i * C_i * L_i \tag{9}$$

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.

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

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.

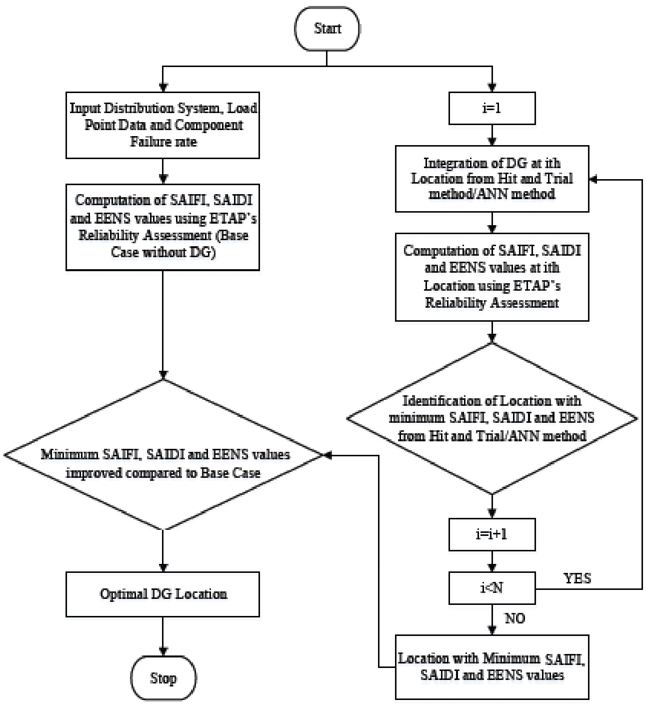

Figure 1: Overall System Methodology

4. Case Studies

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.

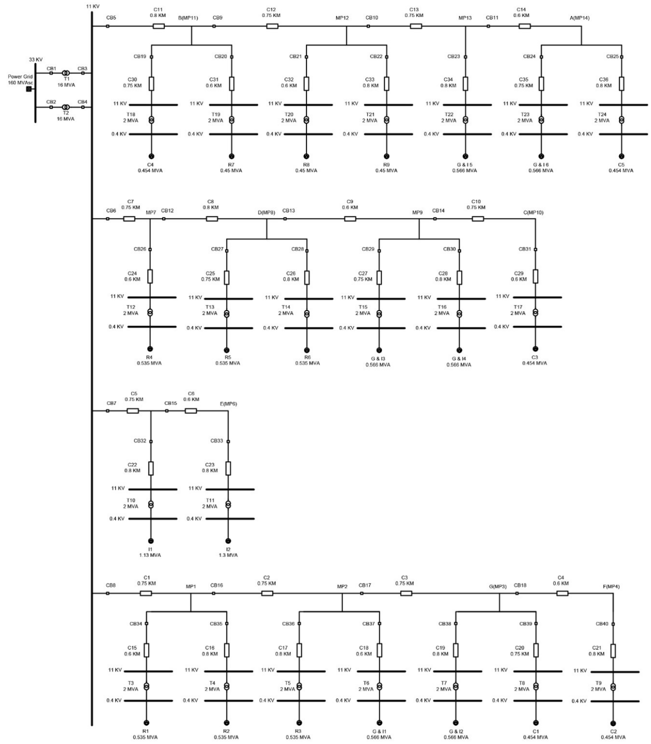

Figure 2: RBTS Bus-2 Distribution System

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

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.

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

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.

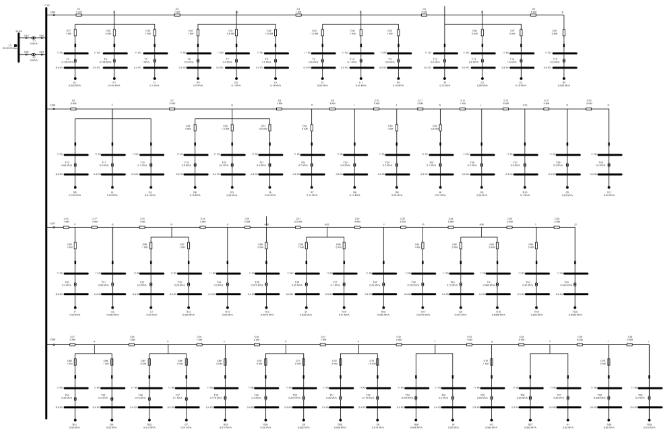

Figure 3: 33/11KV Udipur Distribution feeders.

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

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 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.

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

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

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

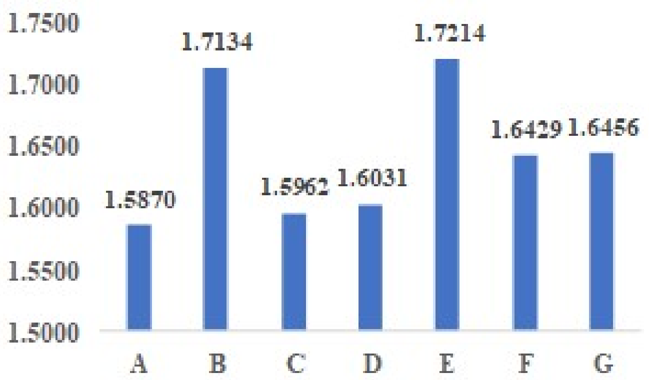

Figure 4: SAIFI values at different locations.

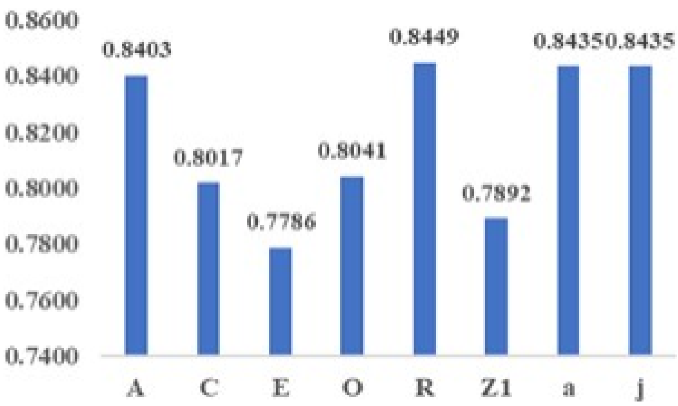

Figure 5: SAIFI Values with DG at different locations

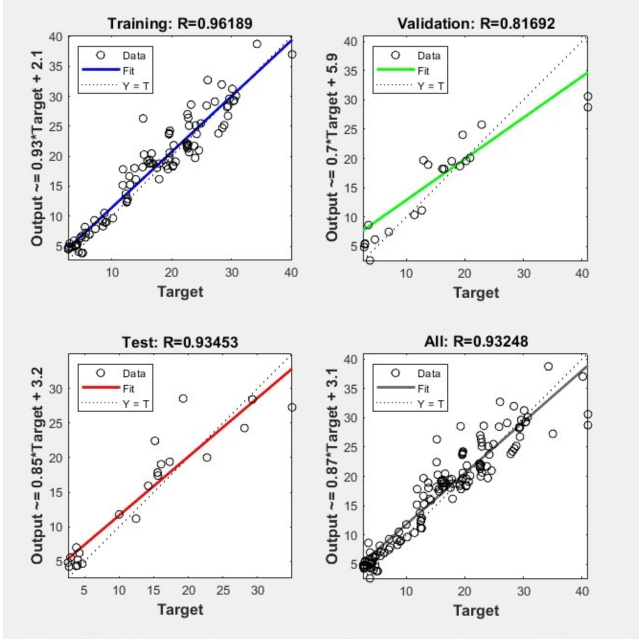

Figure 6: Regression Analysis for testing of ANN model

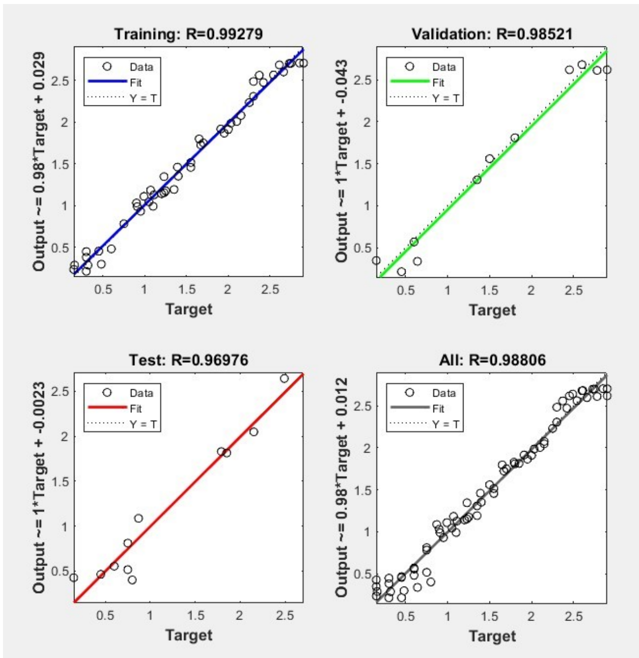

Figure 7: Regression analysis for testing of ANN model

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 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 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.

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

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

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 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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