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Improving Reliability of Active Distribution Networks Using Probabilistic Assessment of Renewable Resource Units

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ABSTRACT

Today, with the growth of the population and increasing trend in the use of electrical energy, the importance of the reliability and stability of the power grid has increased. The ever-increasing development of the power grid and subsequent blackouts of the power grid can lead to serious problems in the daily life and economy of a country. In addition to economic damages, power losses in the power network can lead to dissatisfaction and decreased consumer confidence in the power grid. This research has been carried out to check the application of the genetic algorithm to calculate reliability indices including SAIFI, SAIDI, etc., and its impact on enhancing the reliability of the standard IEEE 33 and 69 bus distribution networks. Additionally, this study explores the GA effectiveness in minimizing both active and reactive power losses. The simulation results in MATLAB, show the constructive effect of applying the GA, shedding light on its potential to optimize the distribution network reliability and minimize power losses, offering valuable insights for power system optimization and reliability improvement.

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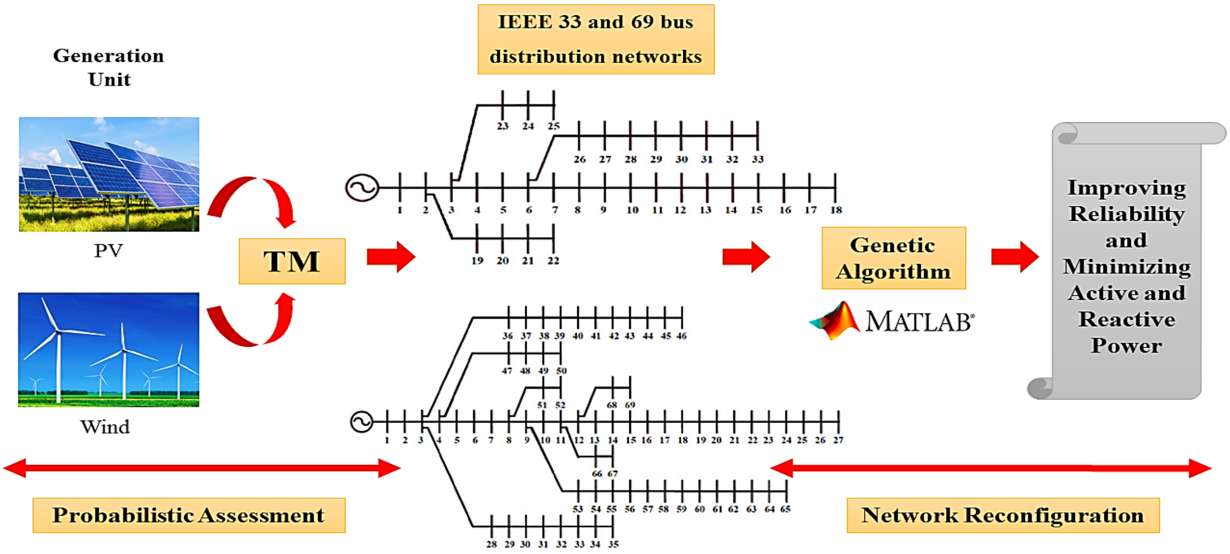
Graphical Abstract



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NOMENCLATURE

V_i^{min} , V_i^{max}	The minimum and maximum voltage in the bus i, respectively	GA, nb-1	Genetic algorithm, All basses except Slack bus, respectively
P_i^{min} , P_i^{max}	The minimum and maximum active power in the bus i, respectively	OA	Orthogonal Arrays
Q_i^{min} , Q_i^{max}	The minimum and maximum reactive power in the bus i, respectively	Level	The value of a random variable is based on an orthogonal array
s_{ij}^{max}	Maximum apparent transmission power	Delta	The main effect of random variables on performance indicators
$T_i^{max}.T_i^{min}$	The maximum, and minimum taps number of transformers, respectively	Rank, TM	Random variable class, and Taguchi method, respectively
$f_{j\psi}$, f^*_{ψ}	The power and the nominal power passing through the ψ transmission line and experiment j, respectively	$V_{i,j}$	The voltage of bus i, and j respectively
N_{exp}, n_g, N_C, N_T, N, N_B, N_L	Number of experiments, generator, compensators, transformers,modules, buses, and lines, respectively	$G_{i,j}$, B_{ij}	Line i – j conductance, and suspension respectively

1. INTRODUCTION

Reliability enhancing, power loss reduction and improving of voltage profile are of great importance for the power network, some or all of these indicators in one or two 14, 30, 32, 33, 38, 57, 69 and 84 bus networks, using Markov processes (1), Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) (2), dynamic reconfiguration of distribution networks with distributed generation (3-5), network stability through controlling the balance of active power between generation and consumption (6), Modified Monte Carlo Simulation (MMCS) (7), roulette wheel selection and the sequential Monte Carlo algorithm (8), Finite Markov Chain Imbedding Approach (FMCIA) and phase-type distributions (9), Multi-Objective Hybrid Teaching–Learning Based Optimization-Grey Wolf Optimizer (MOHTLBOGWO) (10), particle swarm optimization (PSO) (11), backward-forward sweep method (12), advanced Genetic Algorithm (GA) (13), hybrid GWO-PSO (HPSGWO) algorithm (14-16), and Hybrid Particle Swarm Optimization (PSO) and Sea Horse Optimization (PSOSHO) algorithm (17), have been investigated and obtained favorable results.

In addition to the mentioned methods that have been used in several articles, other methods have also been presented in other articles that have led to an enhancing in reliability by optimizing various parameters in the distribution network.

Sandelic et al. (18) discussed about the reliability in microgrid design, especially power electronics challenges. They have supported the adjustment of current reliability methods to better account for these issues.

Also, the reliability implications and stability of combining energy storage systems (ESS) and batteries (2, 6) with grid flexibility options are reviewed, noting the necessity for cyber layer modeling to ensure power system reliability with renewable energy integration (19).

In addition, Kornilov et al. (20) proposed revamping strategies for the power distribution systems of steel-producing plants, to improve reliability and achieve significant economic benefits. Veeramsetty et al. (21) proposed a hybrid genetic dragonfly algorithm to calculate locational marginal prices for distributed generation (DG) buses within a radial distribution system (RDS), aiming to improve reliability by offering incentives to DG units according to their contribution to reliability. Reliability is assessed using the expected energy not supplied metric. The approach allows the distribution company to provide incentives that enhance network reliability. The method is tested on 38-bus and 69-bus RDS models from the Pacific Gas and Electric Company, showing significant reliability improvements when DG units are properly incentivized.

Recently, WSN has also a new challenge to improve reliability and energy efficiency, which is done by efficient and reliable data routing in Wireless Sensor Networks (WSNs) under variable connectivity conditions. This method, which is a genetic algorithm-based method, helps to optimize routing to improve reliability and energy efficiency, which results in fewer data transmissions, reduced energy consumption, minimized delays, and extended network lifespan and the method's effectiveness is validated through simulation metrics such as energy usage, network lifetime, transmission count, and average delivery delay (22).

The remainder of paper is structured as follows: Section 2 introduces the proposed method along with its details. Section 3 details the outcomes of the system's coding using MATLAB and examines these results. A broad discourse on the proposed method and its MATLAB results is covered in Section 4. Finally, section 5 concludes the study with a general conclusion.

2. METHODOLOGY

The objective function of the OPRD problem is minimize network losses as Equation 1 (23).

$$min\sum_{i=1}^{N} a_{2i}\, P_{Gi}{}^{2} + a_{1i}\, P_{Gi} + a_{0i} \qquad (1)$$

where P_L is the total network loss, $P_{Loss,\,l}$ is the total branch loss and nl is the total number of network branches. The minimization of this objective function is bound by various constraints. Equations 2 and 3 show equal limits in the network, in these constraints P_{Gi} and Q_{Gi} are the amount of active and reactive power produced in the slack bus, respectively. P_{Di} and Q_{Di} are also the active and reactive demands of the basses. The denominator Vi indicates the voltage of the bus i as well as the amount of angle difference between the basses and the j. And nb-1 indicates all basses except slack bass. G_{ij} and B_{ij} are also the mutual conduction and suspension between bass i, j. Equations 4 and 5 express unequal constraints including the voltage constraints of generators and transformers tap.

$$V_i \sum_{i=1}^{N} V_j \left(G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}\right) + P_{Di} - P_{Gi} - P_{wi} = 0 \tag{2}$$

$$V_i \sum_{i=1}^{N} V_j \left(G_{ij} \sin \delta_{ij} + B_{ij} \cos \delta_{ij}\right) + Q_{Di} - Q_{Gi} - Q_{ci} = 0 \tag{3}$$

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{4}$$

$$|T_i| \leq T_i^{max} \tag{5}$$

2. 1. Orthogonal Arrays

An (orthogonal array) OA is a fractional factorial matrix whose rows, represent RV levels in each experiment and its columns represent a specific factor. In the past, OA was known as magic squares. The reason OAs are called orthogonal is that all the columns are examined independently. An OA composed of a matrix (Table 1.) that consists of numbers that are arranged in rows and columns. Each row in the matrix is related to an experiment, and in the same way each column corresponds to an RV; then, the dimension of the matrix is ($N_{exp} * N$). L_{ij} corresponds to the level to be appointed to the $\boldsymbol{i^{th}}$ variable in the j^{th} experiment (24).

To use this optimal experiment, one must first express an index according to Bhandari et al. (14):

$$Y_j = \sum_{\psi}^{NL} \left| f_{j\psi} - f^{*}_{\psi} \right| \quad j = 1،2،3، \ldots \tag{6}$$

The second step is to determine the average effect of the factors based on Equations 7 to 12.

The third step is to define the main effect of each factor on Y_j. These main effects of the factors are calculated according to Equations 13 to 15:

$$\bar{A}_1 = (Y_1 - Y_2)/2 \tag{7}$$

$$\bar{A}_2 = (Y_3 - Y_4)/2 \tag{8}$$

$$\bar{B}_1 = (Y_1 - Y_3)/2 \tag{9}$$

$$\bar{B}_2 = (Y_2 - Y_4)/2 \tag{10}$$

$$\bar{C}_1 = (Y_1 - Y_4)/2 \tag{11}$$

$$\bar{C}_2 = (Y_2 - Y_3)/2 \tag{12}$$

$$\Delta A = (\bar{A}_2 - \bar{A}_1) \tag{13}$$

$$\Delta B = (\bar{B}_2 - \bar{B}_1) \tag{14}$$

$$\Delta C = (\bar{C}_2 - \bar{C}_1) \tag{15}$$

If the significant effect is positive in RV or the same factor, the second level is considered otherwise.

It is now shown how to apply the OAs to the POPF by performing the following main steps (25, 26):

a) Determining the input RVs.
b) Determine the number and values of the levels of variables.
c) Determine the OA.
d) Execute load flow.
e) Analysis of results.

All the details of the above-mentioned steps are provided below:

a) RVs of the POPF input are active power and reactive power consumption, wind speed and intensity of sunlight, PV cell temperature.

b) By selecting the variables, the levels of each variable should be determined and it was stated that the number of levels depends on the RV. In this paper, the analysis is performed in two levels using TM (27, 28) and 2PEM and the results are reviewed and compared in terms of accuracy and computational time. By selecting two levels for each random variable, levels 1 and 2 are assumed to be μ - σ and μ + σ, respectively.

c) After determining the number of random variables and the number of levels, it is necessary to select the appropriate OA that the types of OAs are available on the Internet. The number of variables was more or less than the standard OA, so we should choose the closest standard OA and not consider additional variables that unrelated to our problem.

d) After determining the OA, the values determined by the OA are performed for the levels of random variables and load distribution operations, and this process is repeated in a number $Nexp$ proportional to the OA values.

e) Once the load distribution output results are determined, statistical indicators such as mean and

TABLE 1. Orthogonal array $OA_{N_{exp}}\ (N_L)^N$

Experiment number	**Level of each variable**			
	RV$_1$	**RV$_2$**	**…**	**RV$_N$**
1	L_{11}	L_{12}	…	L_{1N}
2	L_{21}	L_{22}	…	L_{2N}
….	….	….	…	….
N_{exp}	LN_{exp1}	LN_{exp2}	…	LN_{expN}

standard deviation are calculated using the following equation:

$$\mu_j = \frac{1}{Nexp}\sum_{i=1}^{Nexp} x_{ji} \quad . \sigma_j = \left[\frac{(\sum_{i=1}^{Nexp} x_{ji} - \mu_i)^2}{Nexp}\right] \tag{16}$$

Where x_{ji} is the value of the j^{th} output RV for the i^{th} experiment.

Figure 1 shows the flowchart of Taguchi Method.

3. RESULTS

In this section, first of all, the best values of μ and σ using probabilistic methods such as Scenario, LHS, and 2PEM have been tested and evaluated according to Table 1, because the Taguchi method has the better values of μ and σ than others three methods, so the Taguchi method has been selected. Tables 2 and 3 present the values of the 33-bus network before and after reconfiguration, respectively. Also, Tables 4 and 5 present the GA and PSO converge graph of the 33-bus network before and after the reconfiguration simulation, respectively. Tables 6 and 7 present the values of the 69-bus network before and after reconfiguration, respectively. Also, Table 8 presents the GA converge graph of the 69-bus network before and after the reconfiguration simulation, respectively. Figures 2 and 3 show the voltage and losses converge profile of the 33-bus network before and after reconfiguration, respectively. Figures 4 and 5 depict the voltage and losses converge profile of 33- bus network before and after reconfiguration, respectively.

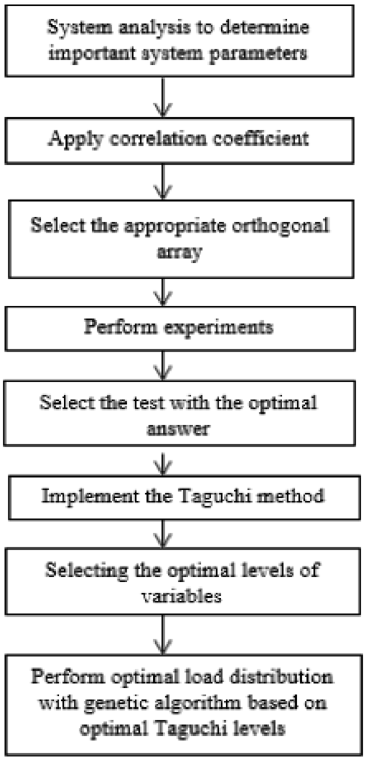

Figure 1. Flowchart of Taguchi Method

TABLE 1. Values of μ and σ using other methods

Entire losses	TM	Scenario	LHS	2PEM
μ [MW]	30.5	40.8	52.42	36.3
σ	11.15	26.1	36.22	12.2

TABLE 2. Loss values before reconfiguration

FROM BUS NODE	TO BUS NODE	P_LOSS_kW	Q_LOSS_kVar
1	2	12/2404	6/2397
2	3	51/7912	26/3789
3	4	19/9005	10/1351
4	5	18/6989	9/5237
5	6	38/2486	33/0180
6	7	1/9145	6/3285
7	8	4/8380	1/5988
8	9	4/1805	3/0035
9	10	3/5609	2/5240
10	11	0/5537	0/1831
11	12	0/8811	0/2914
12	13	2/6662	2/0978
13	14	0/7292	0/9598
14	15	0/3570	0/3177
15	16	0/2815	0/2055
16	17	0/2516	0/3360
17	18	0/0531	0/0417
2	19	0/1610	0/1536
19	20	0/8322	0/7499
20	21	0/1008	0/1177
21	22	0/0436	0/0577
3	23	3/1816	2/1740
23	24	5/1437	4/0617
24	25	1/2875	1/0074
6	26	2/6009	1/3248
26	27	3/3290	1/6950
27	28	11/3009	9/9637
28	29	7/8333	6/8242
29	30	3/8957	1/9843
30	31	1/5936	1/5750
31	32	0/2132	0/2485
32	33	0/0132	0/0205

TABLE 3. Loss values after reconfiguration

FROM BUS NODE	TO BUS NODE	P_LOSS_kW	Q_LOSS_kVar
1	2	11/9154	6/0740
2	3	24/0804	12/2649
3	4	6/3683	3/2433
4	5	5/5320	2/8175
5	6	10/8923	9/4027
7	8	0/2438	0/0806
8	9	1/5404	1/1067
9	10	0/0975	0/0691
10	11	0/0040	0/0013
12	13	0/4535	0/3568
13	14	0/0763	0/1005
15	16	0/2641	0/1929
16	17	0/2361	0/3152
17	18	0/0498	0/0391
2	19	2/7918	2/6642
19	20	22/6307	20/3920
20	21	5/3865	6/2928
21	22	0/6921	0/9150
3	23	3/1515	2/1534
23	24	5/0948	4/0231
24	25	1/2752	0/9978
6	26	2/4885	1/2676
26	27	3/1849	1/6216
27	28	10/8105	9/5314
28	29	7/4931	6/5278
29	30	3/7262	1/8980
30	31	1/5240	1/5061
31	32	0/2039	0/2376
32	33	0/0126	0/0196
8	21	11/4215	11/4215
9	15	1/1336	1/1336
12	22	1/0829	1/0829

TABLE 4. GA results

PARAMETERS	BEFORE RECONFIGURATION	AFTER RECONFIGURATION
'NETWORK TIE SWITCH NUMBER'	'33 34 35 36 37'	'36 6 14 11 37'
'TOTAL POWER LOSS K.W'	'202.6771'	'145.8581'
'MIMIMUM VOLTAGE @ BUS'	'0.91306 @ Bus No 18'	'0.93729 @ Bus No 33'
'MAXIMUM VOLTAGE @ BUS'	'1 @ Bus No 1'	'1 @ Bus No 1'
'EXECTUION TIME'	'2.774'	'3045.4032'
'BEST ITERATION'	'NIL'	'89'
'PERCENTAGE LOSS REDUCTION %'	'NIL'	'28.0342'
'SAIDI(hr/c.yr)'	'2.0436'	'1.5347'
'SAIFI(f/c.yr)'	'2.4126'	'2.1369'
'EENS(KWhr/yr)'	'2066.6446'	'1877.7494'
'AENS(KWhr/C.yr)'	'0.1136'	'0.1032'
'ASAI(p.u)'	'0.99977'	'0.9998'
'AUSI(p.u)'	'0.0002'	'0.0002'
'CAIDI(hr/c.Int.)'	'0.8470'	'0.7182'

TABLE 5. PSO Results

PARAMETERS	BEFORE RECONFIGURATION	AFTER RECONFIGURATION
'NETWORK TIE SWITCH NUMBER'	'33 34 35 36 37'	'36 6 14 11 37'
'TOTAL POWER LOSS K.W'	'215.546'	'161.923'
'MIMIMUM VOLTAGE @ BUS'	'0.91306 @ Bus No 18'	'0.93729 @ Bus No 33'
'MAXIMUM VOLTAGE @ BUS'	'1 @ Bus No 1'	'1 @ Bus No 1'
'EXECTUION TIME'	'3.51'	'3263.521'

'BEST ITERATION'	'NIL'	'93'
'PERCENTAGE LOSS REDUCTION %'	'NIL'	'22.05'
'SAIDI(hr/c.yr)'	'2.163'	'1.5347'
'SAIFI(f/c.yr)'	'2.054	'2.456'
'EENS(KWhr/yr)'	'2579.845'	'1889.832'
'AENS(KWhr/C.yr)'	'0.1285'	'0.1056
'ASAI(p.u)'	'0.99877'	'0.9988'
'AUSI(p.u)'	'0.0005'	'0.0007'
'CAIDI(hr/c.Int.)'	'0.9640'	'0.982'

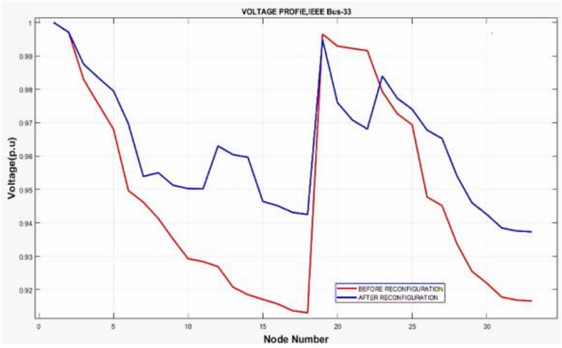

Figure 2. Voltage profile of 33-bus network B/A reconfiguration

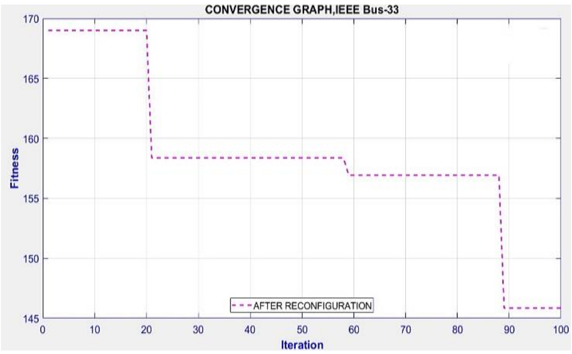

Figure 3. Loss profile of 33-bus network After reconfiguration

Specify Population Value:--10, Specify Iteration Value:--100, Specify IEEE Bus System,33 or 69—69

TABLE 6. Loss values before reconfiguration

FROM BUS NODE	TO BUS NODE	P_LOSS_kW	Q_LOSS_kVar
1	2	0/0750	0/1799
2	3	0/0750	0/1799
3	4	0/1949	0/4678
4	5	1/9364	2/2681
5	6	28/2354	14/3800
6	7	29/3431	14/9449
7	8	6/8933	3/5139
8	9	3/3744	1/7180
9	10	4/7728	1/5775
10	11	1/0138	0/3352
11	12	2/1892	0/7235
12	13	1/2843	0/4239
13	14	1/2454	0/4116
14	15	1/2046	0/3980
15	16	0/2238	0/0740
16	17	0/3204	0/1059
17	18	0/0026	0/0009
18	19	0/1041	0/0344
19	20	0/0669	0/0219
20	21	0/1074	0/0355
21	22	0/0005	0/0002
22	23	0/0051	0/0017
23	24	0/0112	0/0037
24	25	0/0060	0/0020
25	26	0/0025	0/0008
26	27	0/0003	0/0001
3	28	0/0003	0/0009
28	29	0/0026	0/0063
29	30	0/0058	0/0019
30	31	0/0010	0/0003
31	32	0/0051	0/0017
32	33	0/0123	0/0041
33	34	0/0104	0/0034
34	35	0/0005	0/0002
3	36	0/0014	0/0034
36	37	0/0151	0/0369

37	38	0/0173	0/0202
38	39	0/0050	0/0058
39	40	0/0002	0/0002
40	41	0/0487	0/0569
41	42	0/0201	0/0235
42	43	0/0027	0/0031
43	44	0/0005	0/0006
44	45	0/0061	0/0077
45	46	1.2562e-05	1.6749e-05
4	47	0/0233	0/0575
47	48	0/5828	1/4266
48	49	1/6335	3/9970
49	50	0/1159	0/2835
8	51	0/0018	0/0009
51	52	4.3794e-05	1.4700e-05
9	53	5/7812	2/9438
53	54	6/7114	3/4185
54	55	9/1247	4/6458
55	56	8/7901	4/4779
56	57	49/6845	16/6771
57	58	24/4892	8/2183
58	59	9/5057	3/1436
59	60	10/6710	3/2392
60	61	14/0262	7/1444
61	62	0/1121	0/0571
62	63	0/1349	0/0687
63	64	0/6612	0/3368
64	65	0/0412	0/0210
11	66	0/0026	0/0008
66	67	1.5324e-05	4.5647e-06
12	68	0/0233	0/0077
68	69	3.7065e-05	1.2618e-05

TABLE7. Loss values after reconfiguration

FROM BUS NODE	TO BUS NODE	P_LOSS_kW	Q_LOSS_kVar
1	2	0/0720	0/1728
2	3	0/0720	0/1728
3	4	0/0920	0/2208
4	5	0/0180	0/0211
5	6	0/2631	0/1340
6	7	0/2685	0/1367
7	8	0/0469	0/0239
8	9	0/0059	0/0030
9	10	0/0059	0/0019
11	12	0/3052	0/1009
12	13	0/0006	0/0002
14	15	0/0007	0/0002
15	16	0/8424	0/2785
16	17	1/3950	0/4613
17	18	0/0144	0/0049
18	19	0/8122	0/2685
19	20	0/5221	0/1711
20	21	0/8437	0/2788
21	22	0/0205	0/0067
22	23	0/2273	0/0752
23	24	0/4948	0/1636
24	25	0/9168	0/3030
25	26	0/3782	0/1250
26	27	0/1953	0/0645
3	28	0/0003	0/0009
28	29	0/0026	0/0063
29	30	0/0058	0/0019
30	31	0/0010	0/0003
31	32	0/0051	0/0017
32	33	0/0123	0/0041
33	34	0/0104	0/0034
34	35	0/0005	0/0002
3	36	0/0665	0/1632
36	37	0/9281	2/2694
37	38	1/4636	1/7096
38	39	0/4225	0/4934
39	40	0/0240	0/0280
40	41	9/3378	10/9097
41	42	3/9659	4/6350
42	43	0/5245	0/6115
43	44	0/0502	0/0633
44	45	0/5939	0/7488
45	46	0/0044	0/0059
4	47	0/1658	0/4097
47	48	4/1508	10/1600
48	49	13/1674	32/2188
49	50	2/5254	6/1783
8	51	0/0017	0/0009

51	52	4.2118e-05	1.4136e-05
9	53	0/0050	0/0025
53	54	0/0049	0/0025
54	55	0/0016	0/0008
55	56	0/0000	0/0000
56	57	0/0000	0/0000
57	58	0/0000	0/0000
59	60	6/2423	1/8949
60	61	8/2051	4/1793
62	63	0/0015	0/0008
63	64	0/0075	0/0038
64	65	0/7157	0/3645
11	66	0/0026	0/0008
66	67	0/0000	0/0000
12	68	0/0228	0/0075
68	69	3.6256e-05	1.2342e-05
11	43	0/7478	0/7478
15	46	4/3883	2/1942
50	59	37/7035	18/8517
27	65	1/0351	0/5175

TABLE 8. GA results

PARAMETERS	BEFORE RECONFIGURATION	AFTER RECONFIGURATION
'NETWORK TIE SWITCH NUMBER'	'69 70 71 72 73'	'13 70 58 10 61'
'TOTAL POWER LOSS K.W'	'224.9606'	'104.3281'
'MIMIMUM VOLTAGE @ BUS'	'0.90901 @ Bus No 65'	'0.94947 @ Bus No 61'
'MAXIMUM VOLTAGE @ BUS'	'1 @ Bus No 1'	'1 @ Bus No 1'
'EXECTUION TIME'	'3.483'	'10851.7595'
'BEST ITERATION'	'NIL'	'15'
'PERCENTAGE LOSS REDUCTION %'	'NIL'	'53.6238'
'SAIDI(hr/c.yr)'	'1.0086'	'0.8383'
'SAIFI(f/c.yr)'	'1.5354'	'1.0889'
'EENS(KWhr/yr)'	'7803.8025'	'2934.1119'
'AENS(KWhr/C.yr)'	'0.6268'	'0.2357'
'ASAI(p.u)'	'0.9999'	'0.9999'
'AUSI(p.u)'	'0.00011514'	'9.5694e-05'
'CAIDI(hr/c.Int.)'	'0.6569'	'0.7698'

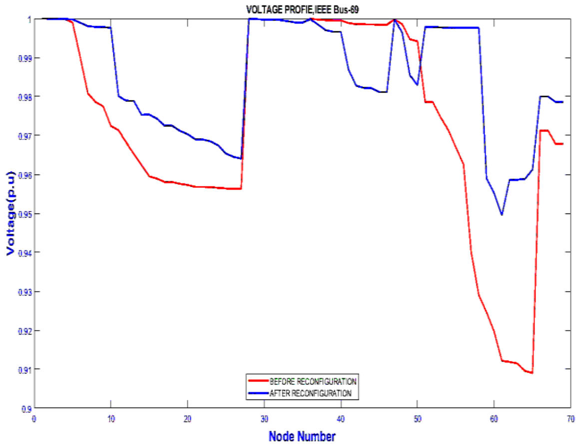

Figure 4. Voltage profile of 69-bus network B/A reconfiguration

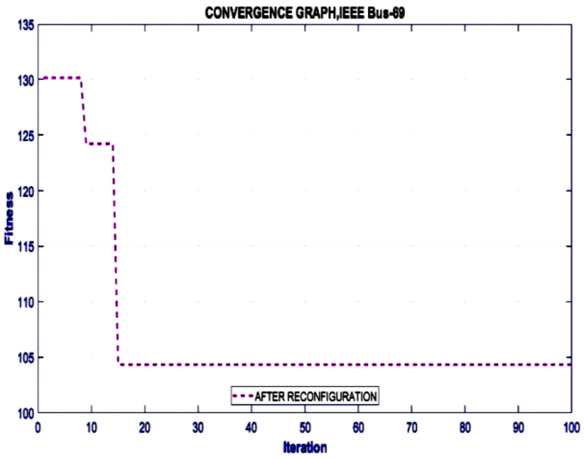

Figure 5. Loss profile of 69-bus network After reconfiguration

4. DISCUSSION

The research explores the application of the genetic algorithm (GA) to enhance the reliability of standard IEEE 33 and 69 bus distribution networks and to minimize power losses. The study focuses on calculating reliability indices, including SAIFI, SAIDI, and the impact of the GA on enhancing the reliability of the distribution networks. Additionally, the effectiveness of the GA in minimizing both active and reactive power losses is investigated. The simulation results in MATLAB demonstrate the constructive effect of applying the GA, shedding light on its potential to optimize the distribution network reliability and minimize power losses, offering valuable insights for power system optimization and reliability improvement.

5. CONCLUSION

The results emphasize the efficacy of reconfiguration in minimizing power losses and enhancing system performance in both IEEE-33 and IEEE-69 bus systems.

The initial power loss before reconfiguration in the IEEE-33 bus system was 202.6771 kW, which was reduced to 145.8581 kW after reconfiguration, indicating a significant reduction of 28.0342%. Additionally, system performance metrics such as SAIDI, SAIFI, EENS, and AENS showed improvement, highlighting the effectiveness of reconfiguration in enhancing system reliability and efficiency. In the case of the IEEE-69 bus system, the initial power loss before reconfiguration was 224.9606 kW, which was reduced to 104.3281 kW after reconfiguration, signifying an impressive reduction of 53.6238%. Similar to the IEEE-33 bus system, system performance metrics exhibited substantial improvement, including a notable decrease in SAIDI and SAIFI, and enhancements in EENS and AENS. The study underscores the potential of reconfiguration strategies to improve the efficiency, reliability, and voltage stability of power distribution networks. The simulation results in MATLAB show a significant reduction in power losses after reconfiguration, along with improvements in system performance metrics such as SAIDI, SAIFI, EENS, and AENS. These findings highlight the potential of reconfiguration strategies to enhance the reliability and efficiency of power distribution networks, positioning them as valuable contributions to power system optimization and reliability improvement.

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Persian Abstract

چکیده

امروزه با رشد جمعیت و افزایش استفاده از انرژی الکتریکی، اهمیت قابلیت اطمینان و پایداری شبکه برق افزایش یافته است. توسعه روزافزون شبکه برق و متعاقب آن خاموشی شبکه برق می تواند منجر به مشکلات جدی در زندگی روزمره و اقتصاد یک کشور شود. تلفات برق در شبکه برق علاوه بر خسارات اقتصادی می تواند منجر به نارضایتی و کاهش اعتماد مصرف کننده به شبکه برق شود. این تحقیق به منظور بررسی کاربرد الگوریتم ژنتیک برای محاسبه شاخص‌های قابلیت اطمینان شامل SAIFI، SAIDI و غیره و تأثیر آن بر افزایش قابلیت اطمینان شبکه‌های توزیع استاندارد IEEE ۳۳ و ٦۹ باس انجام شده است. علاوه بر این، این مطالعه اثربخشی GA را در به حداقل رساندن تلفات توان فعال و راکتیو بررسی می‌کند. نتایج شبیه‌سازی در MATLAB، تأثیر سازنده به‌کارگیری GA را نشان می‌دهد، پتانسیل آن را برای بهینه‌سازی قابلیت اطمینان شبکه توزیع و به حداقل رساندن تلفات توان، روشن می‌کند، و بینش‌های ارزشمندی را برای بهینه‌سازی سیستم قدرت و بهبود قابلیت اطمینان ارائه می‌دهد.