DISTRIBUTION NETWORK RECONFIGURATION USING GENETIC ALGORITHM FOR LOSS REDUCTION: A CASE STUDY OF KATUNJE FEEDER, BHAKTAPUR

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Abstract

The power distribution system has difficulties with regard to power loss and unacceptable voltage drops as a result of the rapidly expanding power system network, rising electrical energy consumption, and longer distances of power distribution. A typical strategy to address the issues with the distribution system is to perform distribution system reconfiguration. The study focuses on distribution feeder reconfiguration of the Katunje Feeder of Bhaktapur, Nepal where optimization problem is formulated to minimize the system active power loss and investment cost of the system. Genetic algorithm is employed in a co-simulation framework to solve the optimization problem where states of 26 different tie switches are to be altered to achieve the desired optimum results. Two cases are formulated: in case I active power loss is assigned more weight than investment cost whereas, in case II equal weights are assigned for active power loss and investment cost. The results showed the reduction in active power loss and investment cost for both the cases. Case I resulted in more active power loss reduction compared to case II, and case II resulted in more investment cost reduction compared to case I. From this, decision makers can obtain insights in adopting one of the cases for distribution feeder reconfiguration based on technical consideration (active power loss reduction) or economic consideration (investment cost reduction).

Keywords: Distribution network reconfiguration, Metaheuristic, Genetic algorithm, Co-simulation.

1. Introduction

Distribution system is a vital portion of an electrical power system network that facilitates the delivery of electrical power to the consumers. They comprise of main feeders and laterals that constitute the link between the subtransmission power system and the consumers. In contrast to the transmission system, distribution system operates at low voltage and high current, Distribution networks also have high value of resistance compared to the inductive reactance of the line resulting in high power loss and issues with the voltage regulations (Naik et al., 2013). Furthermore, with the rapid expansion of power system network, increasing demand of electrical energy and increased length of power distribution, power distribution system faces challenges with respect to power loss and unacceptable voltage drops. General strategies adopted to address the issues regarding the power loss and voltage regulation in distribution networks include feeder reconfiguration, reinforcement of feeders, construction of new substations, reactive power compensation, installing voltage regulators, distributed generation (DG) hosting (Abdelkader and Elshahed, 2021; Gallego Pareja et al., 2023).

Distribution network reconfiguration (DNR) is a method of uncovering new network topology for the system in order to minimize the system loss, enhance the voltage profile and increase the reliability of the distribution system thereby making the distribution system more efficient and

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robust (Razavi et al., 2022). The general strategy for the DNR is to alter the states of the sectionalizing tie switches that are normally open or closed in the system optimally. However, to alter the states of the sectionalizing tie switches only would be unpractical in the case of heavily loaded radial distribution systems (Salau et al., 2020). DNR is a mathematical optimization problem, and to be precise, it is a mixed integer non-linear (MINL) problem. Further, DNR is a non-convex optimization problem with a large number of possible network topologies resulting from the combination of each switch status in the system.

The optimization problem formulation for DNR constitutes the constraints that reflect the limitations of the electrical parameters and also the limitations regarding the topology of the network. Thereby, metaheuristic optimization algorithms could be suitable techniques to solve the non-convexity and non-linear nature of the DNR problem. Application of a meta-heuristic algorithm for solving such optimization problems eliminates the requirement of convexifying the non-convex problem (Stojanović et al., 2017). Several literature and research works underline the application of meta-heuristic algorithms for solving optimization problems related to DNR in a power system network (Swarnkar et al., 2011; Helmi et al., 2021; Ganesh and Kanimozhi, 2018).

Genetic algorithm (GA) is a metaheuristic optimization technique inspired by the process of natural selection. It is extensively used in electrical engineering to tackle linear as well as non-linear and non-convex optimization problems (Hernández Valencia et al., 2021). Various research and literature highlight the application of GA in order to solve combinatorial optimization problems, such as a distribution network reconfiguration problem and for solving associated with the power system network (Abdelaziz, 2017; Gupta et al., 2010; Huang, 2002; Zhu, 2002; D. et al., 2017). Further, meta-heuristic algorithms, like GA, offers global search capability where it can explore a wide solution space and find global optima. This is the requirement of the DNR problems where the optimization problem to be solved is complex and multi-objective. Also, GA can handle both continuous and discrete variables, provides optimization flexibility that can have potential benefits in formulating the optimization problem based on desired requirements, and can be scaled to large problems making it suitable to work with DNR problems where the distribution system comprises of number of nodes, lines and combination of network topologies (Zhu, 2002; Kahouli et al., 2021).

A non-dominated sorting genetic algorithm to solve the multi-objective distribution network reconfiguration problem considering the minimization of real power losses, enhancement of voltage profile and load balancing is proposed in (Eldurssi and O'Connell, 2015). The suggested algorithm for the DNR problem in this case offers a number of potential solutions for the reconfiguration, among which the system planner must decide. Furthermore, various variants and hybrid application of the GA have been employed for DNR problems. In Zhu (2002), the author presented a refined GA for DNR where the main objective was to minimize the power loss. It was tested in IEEE 16 and IEEE 33 bus systems respectively where a radiation distribution network load flow (RDNLF) method was also employed to obtain accurate branch currents in the distribution network. The refined GA in the study adopted an adaptive mutation approach that prevents the premature convergence of the optimization problem, and the proposed algorithm was able to reach global optimum value.

In a conventional GA approach for network reconfiguration, huge amount of unfeasible solutions is generated after crossover and mutation thereby resulting in low search efficiency. A genetic algorithm approach to the DNR problem motivated by graph theory is presented in (Zhang et al., 2014). Here, a spanning tree is used to generate tie branches, and each spanning tree is connected to a particular GA subgroup. The key benefit of this method is that search efficiency is greatly increased and infeasible solutions are not created during the reconfiguration phase of the GA, and search efficiency is highly improved. Additionally, in Gupta et al. (2010), the authors presented a method for reconfiguration of radial distribution network in fuzzy framework and is inspired by graph theory. The DNR problem addressed in the study is a multi-objective optimization problem that makes use of an adaptive genetic algorithm. The initial population for the genetic algorithm is created using a heuristic approach, and the genetic operators are modified with the aid of graph theory to produce viable individuals. The proposed method reduces computational burden and the study examined the effectiveness of the method on 70-bus test system and 136-bus real distribution system.

Distribution system faces reliability and power quality issues in a deregulated and competitive environment where the reliability of the distribution system involves the contingencies associated with all terminals and protection equipment and the distribution feeders (Brown et al., 2001). An efficient GA approach to improve the reliability and power quality of distribution networks using network reconfiguration is proposed in Gupta et al. (2014). Here, objective function for the optimization is formulated by addressing power quality and reliability issues for the reconfiguration problem. For this, several objectives such as feeder power loss, system's node voltage deviation, system's average interruption frequency index, system's average interruption unavailability index and energy not supplied regarding the power quality and reliability are taken into account. The efficacy of the proposed method is tested on IEEE 33 bus and IEEE 69 bus system and the study highlights the effectiveness of the proposed algorithm when compared to the existing GA based approaches. Additionally, an enhanced GA approach for distribution network reconfiguration to address power loss reduction and reliability improvement is presented in Duan et al. (2015). The presented method has improved crossover which is employed on IEEE 33-bus, IEEE 69-bus and IEEE 136-bus radial distribution system, and the results showed that the proposed method for DNR is computationally fast with better accuracy compared to conventional approach. Also, the final optimal value obtained through the enhanced GA ensured that the network topology remains radial.

The study aims to perform distribution network reconfiguration for Katunje feeder of Bahktapur, Nepa,l using genetic algorithm. This study takes into account the minimization of active power loss and investment cost for the reconfiguration problem of the distribution feeder. Two cases are formulated for the re-configuration problem followed by the analysis of the results obtained.

2. Methodology

Methodology section is divided into three sections. First section covers the description of site for case study, while other two sections deal with problem formulation and solution to the optimization problem. Their details are presented in the forthcoming sections.

2.1. Study case selection

The study presents distribution feeder reconfiguration of Katunje feeder at Bhaktapur substation, Nepal. This feeder is located in urban part of Nepal and has huge possibilities of re-routing. The specifications and a Geographical Information System (GIS) file of the feeder were obtained from Nepal Electricity Authority (NEA). The feeder begins from Bhaktapur substation with elongation of around 20.53 Km (calculated using GIS) with many branches making it as a radial feeder in the base case. Throughout its length, the total size of connected transformers is 8790 kVA.

The transformers around the vicinity of 50 meters are lumped together into a single bus that results in 43 nodes or bus in the distribution feeder with voltage level of 11 kV. The information of the bus is presented in the Table 1, followed by this the single line diagram (SLD) of the distribution feeder originating from Bhaktapur substation as shown in Figure 1.

With the observation from GIS map of the feeder, 26 possible routes for the distribution network reconfiguration is obtained. All of these 26 possible routes are to be connected by tie line switches and will be taken into account for the optimization problem formulation of the study for DNR. The information of the tie line switch is presented in Table 2.

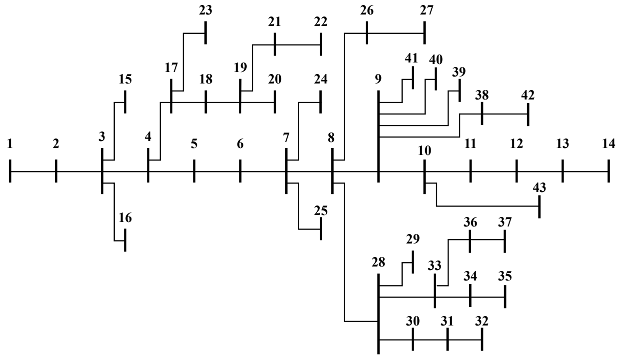

Figure 1. Single line diagram of Katunje feeder

2.2. Problem formulation

Although there are 26 possible switches as seen from GIS, it is not possible to close them all to re-route the power because of its complexity in switching and also the investment cost. Therefore, the main problem here is to minimize the active power loss as well as investment cost so that the reconfigured network could be easily implemented in real world scenario which would be technically and economically viable. For the formulation of the optimization problem, the objective is to minimize the system active power loss and investment cost. The mathematical formulation of the optimization problem for the distribution feeder reconfiguration is presented from Equation (1) to (4). The active power loss and investments costs are assigned with weight for minimization problem formulation.

Here, the problem is subjected to a number of switches to be closed which are bounded between 0 and 5 as shown in the constraint of the optimization problem that is presented in Equation (3). The upper value for a number of switches to be closed is selected to be 5 to make the optimization problem simpler and computationally efficient. The number of switches to be closed belongs to the set of number of possible tie switches (i.e. 26 switches).

$$F_{obj} = Minimize\{F_1 \times WL + F_2 \times WC\} \tag{1}$$

In Which,

$$[F_1, F_2] = \left[\frac{1}{P_{base}} \sum_{i=1}^{N(Br)} P_i^{Loss} \, , \, \frac{1}{C_T} \sum_{j=1}^{N(SC)} C_j \right] \tag{2}$$

Subjected to:

$$0 \leq N(SC) \leq 5 \tag{3}$$

Such that,

$$N(SC) \in \{TS_1, TS_2, TS_3, ...TS_{26}\} \tag{4}$$

Where,

F_{obj} is the objective function based on power loss and investment cost

Table 1. Bus code number

Node Name	Node Numbering
Bhaktapur Substation	1
Ittapako	2
Sallaghari Chowk	3
Sallaghari Pul	4
Katunje Dobato	5
Subrna Chowk	6
Shahara Shop Ind	7
Ghalante	8
Suryabinayak Chowk	9
Adarsha Chowk	10
Bagmati Cold Store	11
Bagmati Club	12
Arpan Deri Nera	13
Valley Poly Marse	14
Ibamura Hospital	15
Sallaghari Srijana Chaour	16
Sallaghari Tinkune	17
Himalayan Net Beer	18
Katunje Mata Ghar Mathi	19
Katunje Ukalo	20
Katunje Sushila Bhairab	21
Katunje Thapa Tole	22
Shrestha Woolen	23
Chundevi Mandir	24
Chundevi Height	25
Barahi Hall	26
Chundevi Police Beat	27
Army Barek Muni	28
Pandubazar Turture Dharo	29
Suryabinayak Army Barek	30
Suryabinayak Ukalo	31
Sipadol Forest office najik	32
Katunje Janasasthya Nera	33
Katunje Chauki	34
Kiwachowk Jane Bato	35
Katunje Ashami Tole	36
Subarneshwor Khane Pani	37
Bhulacha	38
Barahistha Chowk	39
Thapa Party Palace	40
Bhulancha	41
Kalancha	42
Jagati	43

P_i^{Loss} is the active power loss at ith branch
P_{base} is the total system active power loss at base case
$N(Br)$ is the total branches in the network
WL is the weight of loss for optimization
C_j is the investment cost required for jth reconfigured line
C_T is the total investment cost if all 26 switches are closed
$N(SC)$ is the total number of switches to be closed

Table 2. Possible tie feeders' configurations

From bus	To bus	Length(Km)	Indication
2	15	0.32	TS1
15	4	0.23	TS2
15	5	0.36	TS3
15	6	0.44	TS4
16	23	0.24	TS5
16	17	0.38	TS6
22	35	0.34	TS7
5	28	1.10	TS8
5	20	0.35	TS9
20	34	1.05	TS10
21	34	0.33	TS11
6	28	0.89	TS12
40	31	0.47	TS13
40	13	0.74	TS14
40	11	0.75	TS15
40	30	0.75	TS16
40	10	0.84	TS17
32	14	0.64	TS18
8	39	0.26	TS19
8	40	0.53	TS20
7	27	0.10	TS21
25	28	0.33	TS22
28	37	0.72	TS23
42	10	0.37	TS24
42	11	0.43	TS25
11	43	0.31	TS26

WC is the weight of investment cost for optimization

2.3. Problem solving approach

The optimization problem formulated in the aforementioned section is a non-convex problem. A mathematical optimization approach to the above problem would be complex where relaxing the non-convex problem would result in complexity of the problem in terms of problem formulation and computation. Hence, meta-heuristic optimization would be a viable option for solving the non-convex optimization problem (Aghay and Alqallaf, 2019). Genetic algorithm (GA) is selected for the study to minimize the active power loss and investment cost of the Katunje feeder for distribution feeder reconfiguration. GA is a global search algorithm that can find the best solution for given optimization problem although the problem has multiple local minima. Furthermore, GA is robust that can take into account a wide variety of constraints, and fast that can solve problems with reasonable computation time (McCall, 2005). The flow chart of GA is presented in Figure 2. Solving problem with GA includes three steps, in the beginning initialization and chromosomes generation, then after cross-over and finally the mutation process. The initialization of population size, number of generations and number of bits, cross-over probability and mutation probability, weightage for loss and weightage for cost are performed in the primary step of the algorithm. In the next step, generation of numbers of chromosomes equals to number of population size with length equal to number of bits is to be carried out. Here, number of bits represents the tie switches to be closed. Additionally, fitness value for all the chromosomes is to be calculated and minimum fitness values is saved as the global best solution. Global best solution contains the switch numbers to be closed, active power loss and investment cost. Followed by this is reproduction stage that includes cross-over and mutation. To reproduce the chromosomes, crossover and mutation in accordance to the mutation probability is to be performed for every generations. For each generation, reproduction is to be carried out for number of times (i.e. equals to the population size). For each reproduction, computation of fitness value is to be carried out and compared with previous global best value. If the new fitness value is less than the global best value then global best value is to be updated.

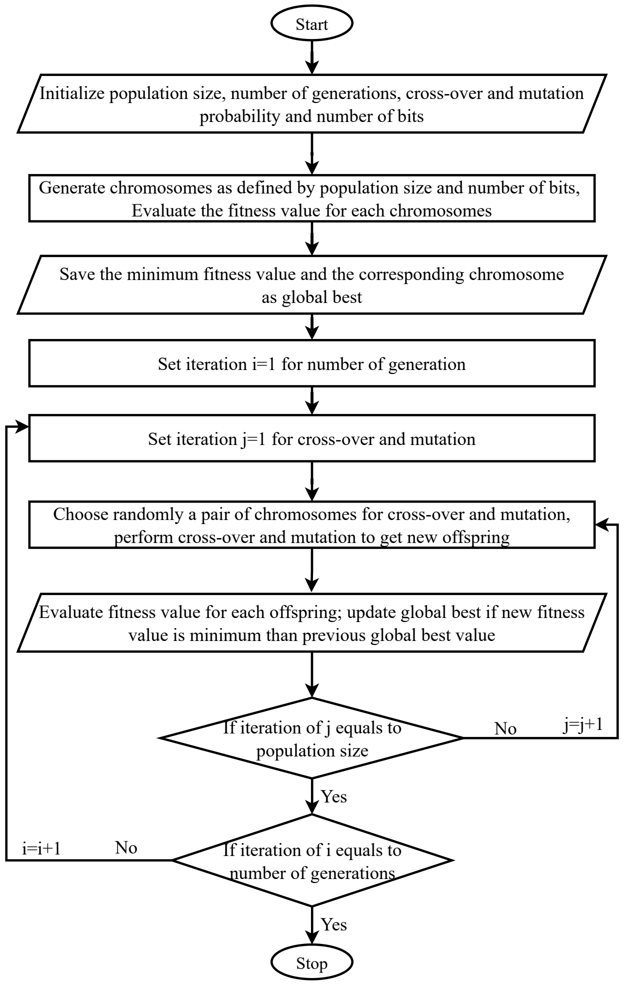

Figure 2. Flow chart of Genetic Algorithm

In order to calculate power loss, Digsilent Powerfactory software was used. All the calculation except load flow was performed in MATLAB. The investment cost to construct per Km of distribution line using DOG conductor was taken by consulting the NEA. The overall process for calculating fitness value is shown in Figure 3.

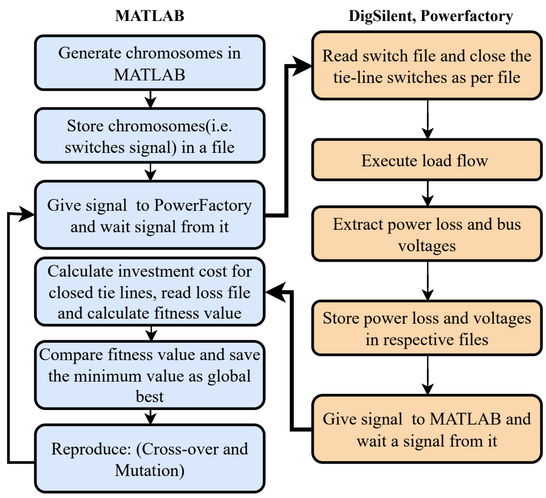

Figure 3. Block diagram of co-simulation between DiGSILENT and MATLAB

In Figure 3, the real distribution feeder was modeled in the Powerfactory software whereas MATLAB is used to calculate the optimized value for the optimization problem using GA. The study presents a co-simulation framework with DigSilent Powerfactory and MATLAB for the distribution feeder reconfiguration where the objective function value (i.e. active power loss values) is obtained from Powerfactory and the optimization problem is solved in MATLAB. All the possible tie lines (obtained from GIS) for reconfiguration was connected using tie switches. The number of tie switches to be closed was generated in the MATLAB and is sent to PowerFactory software. In the same time, the investment cost required to construct the lines if those switches are closed was calculated. In Powerfactory, the mentioned switches were closed and load flow was carried out. Then, active power loss and voltages at each bus were calculated and sent to MATLAB. Using the active power loss and investment cost fitness value would be calculated using cost and power loss weightage (WC and WL). The study is carried out for two cases where each case is defined by its own weights assigned for active power loss and investment cost minimization problem.

3. Results

The optimization was carried out using a co-simulation framework between MATLAB and DiGSILENT PowerFactory. The co-simulation was performed in Intel core i5 processor having 8 GB of RAM. Genetic Algorithm (GA) was used for solving the optimization problem by forming two different cases (Case I and Case II) and the used parameters for co-simulation are shown in Table 3. The co-simulation was carried out for 100 generations with 30 independent runs. The best fitness values after 100^{th} generation for every independent run for two cases is shown in the Figure 4.

Table 3. Parameters initialization for optimization

Parameters Name	For Case I	For Case II
Population size	30	30
Maximum number of generations	100	100
Number of bits	5	5
Cross over probability	95%	95%
Mutation probability	5%	5%
WL & WC	70% & 30%	50% & 50%

Figure 4 shows the optimum fitness value of different independent runs for both cases (i.e. case I and II). The case I has its weightage assigned for active power loss and investment cost as 0.7 and 0.3 respectively whereas, for case II, the weight assigned for active power loss and investment cost is 0.5 and 0.5 respectively. For case I, the best fitness value out of 30 independent runs was found to be 0.507 and it was repeated 3 times. Whereas for case II, the best fitness values were found to be 0.3947, and it was repeated 22 times.

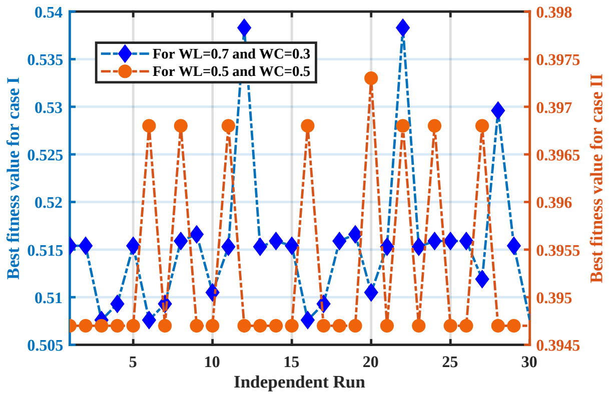

Figure 4. Best fitness values for different independent runs for two cases

Although, repetition of best fitness values for two cases differs, all of the values in each independent run for both the cases could be assumed to be approximately equal. To measure their central tendency, mean, median, standard deviation and mode were calculated.

The measurement of central tendency for 30 independent runs in case I and case II is shown in Table 4. It is observed that the value of mean is 0.5155 and 0.3925 for case I and case II respectively. This the value of median is 0.5145 and 0.3947 for case I and case II respectively. Further, the values of standard deviation for two case were 0.75% and 0.1% respectively. It could be considered that the best fitness value for case I differs more than case II from mean value. The mode for different cases was also approximately equal to mean and median. So, all the independent runs could be approximated as the optimum values, but selection of best out of best value could result best minimization of the problem.

Table 4. Measurement of central tendency

Parameters	For Case I	For Case II
Mean	0.5155	0.3952
Median	0.5154	0.3947
Standard Deviation	0.0075	0.0010
Mode	0.5159	0.3947
Convergence time (minutes)	49.98	52.01

Out of 30 independent runs, the best fitness value was observed in the 16^{th} independent run for case I which is approximately around 0.5076. Similarly for case II, the best fitness value was approximately around 0.3947. The average time for convergence of optimization for case I and case II was around 49.98 minutes and 52.01 minutes respectively. The convergence curve of GA optimization for different cases is presented in Figure 5. From this figure, it is observed that the optimization was converged early before 20^{th} generations.

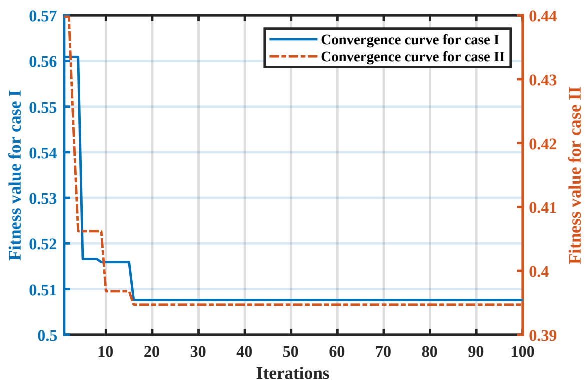

Figure 5. Convergence curve for two cases

The best out of best results was taken as the optimized result and is tabulated in Table 5. For Case I, the fitness value would be minimum if the tie-switches TS1, TS4, TS6, TS20 & TS24 are closed keeping all other switches opened. The power loss would be reduced to 346.49 kW with the investment cost of 31.38 Lakhs NPR for reconfiguration. Similarly for case II, just by closing TS1, TS20 & TS24 would yield the minimum fitness value. In this case, the power loss could be reduced to 366.68 kW with just the investment cost of NPR 18.71 Lakh .

The single line diagram for the reconfigured network for case I is shown in Figure 6. The newly proposed line for

Table 5. Optimized results for two cases

Results	Case I	Case II
TS to close	TS1, TS4, TS6 TS20, TS24	TS1, TS20 TS24
Power loss (kW)	346.49	366.68
Cost (Lakh NPR)	31.38	18.71

reconfiguration for Katunje feeder is shown by red dotted line. There would be five different loops in the feeder after reconfiguration where the control mechanism of tie-feeders for those loops is not presented in the study. The five tie-feeders here are the feeders between Ittapako bus to Ibamura hospital bus of 0.32 Km, Ibamura hospital bus to Subarna chowk bus of 0.44 Km, Sallaghari srijanagar chour bus to Sallaghari tinkune bus is 0.38 Km, Ghalate bus to Thapa party palace bus is 0.53 Km, and Kalancha bus to Aadarshar chowk is 0.37 Km. The total length for reconfiguration is around 2.04 Km.

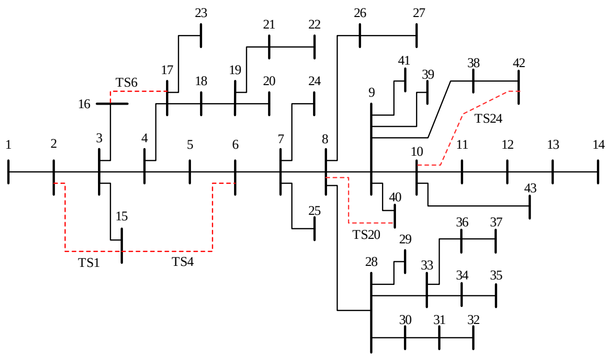

Figure 6. Reconfigured single line diagram for case I

Similarly, the single line diagram of reconfigured network for case II is shown in Figure 7. Again the reconfigured tie-feeders are shown by red dotted lines. These tie-feeders are basically from Ittapako bus to Ibamura hospital bus of 0.32 Km, Ghalate bus to Thapa party palace bus of 0.53 Km and Kalancha bus to Aadarshar chowk of 0.37 Km. This case results the addition of around 1.22 Km tie-feeders making the distribution lines having three loops.

After identifying the reconfiguration lines for case I and case II, the feeder's voltage profile was studied and compared with base case. The load flow was performed using DiGSILENT PowerFactory at base case (i.e. network without any tie-feeders) and active power loss and voltage at each node were observed. The active power loss at base case was found to be 525.56 kW and minimum voltage to be 0.919 p.u. at bus number 14, i.e. Valley Poly Marse bus. The comparison of voltage profile for base case, of case I and case II is shown in Figure 8. The minimum voltage was found improved for both the cases. For case I, the minimum voltage was at bus number 14, and it was 0.951 p.u. whereas for case II, the minimum voltage is 0.944 p.u. in the same

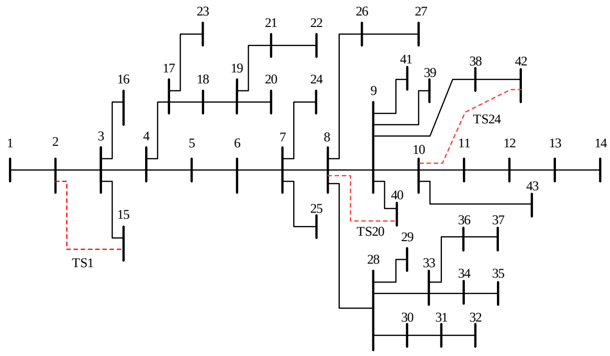

Figure 7. Reconfigured single line diagram for case II

bus.

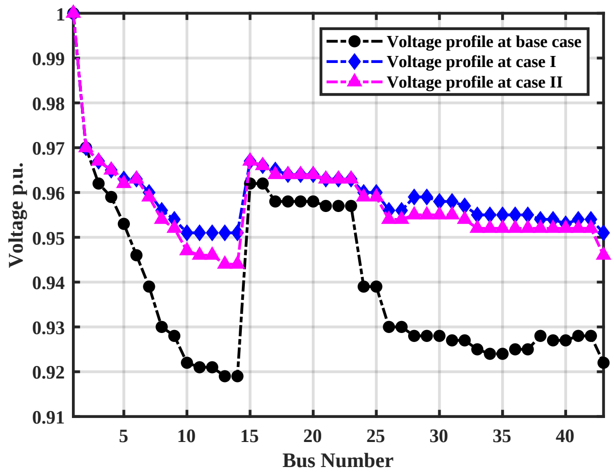

Figure 8. Voltage profile before and after re-configurations

4. Discussion

All the results obtained could be taken positive. The active power loss after reconfiguration was reduced by around 34% and 30% of base case loss for case I and case II respectively. The voltage profile of the feeder was also found to be improved after reconfiguration in both the cases. Although both cases could be chosen for reconfiguration, other parameters like cost and geography should be considered. If technical complexity is the major concern, then it would be better to choose case II which will form just three loops after reconfiguration. Also, investment cost for this case is lesser than that for case I. If technical complexity is not the major concern, then it would be better to choose case I, in which five loops would be formed. The demerit of this case is that, its startup cost is slightly expensive. Therefore, cases should be chosen wisely because addition of more number of tie-feeder would result in reduced active power loss, increased investment cost and add more complexity in control.

5. Conclusion

The DNR was performed in Katunje Feeder which is a radial feeder extended form Bhaktapur Substation. The optimization problem was created with two different cases. Case I was formulated by assigning 70% weightage for loss and 30% for investment cost whereas case II by 50% each. As an optimized result, 5 and 3 tie feeders were determined for the first and second case respectively. Those tie feeders are expected to be added in the network by selecting any one of the cases mentioned above. For case I the total investment cost was found to be NPR. 38.31 Lakh and NPR. 18.71 Lakhs for next case. The result for both the cases could be assumed to be feasible in the sense that loss was reduced by 34% and 30%. The study could be helpful for decision makers while performing distribution feeder reconfiguration in which decision makers could adopt case I or case II based on the technical or economic priorities.

6. Acknowledgment

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References

Abdelaziz, M. (2017). Distribution network reconfiguration using a genetic algorithm with varying population size. *Electric Power Systems Research*, *142*, 9–11.

Abdelkader, Z., M.A.and Osman, & Elshahed, M. (2021). New analytical approach for simultaneous feeder reconfiguration and DG hosting allocation in radial distribution networks. *Ain Shams Engineering Journal*, *12*(2), 1823–1837. https://doi.org/https://doi.org/10.1016/j.asej.2020.09.024

Aghay, K. S. H., & Alqallaf, A. K. (2019). Solving non-convex economic load dispatch problem via artificial cooperative search algorithm. *Expert Systems with Applications*, *128*, 14–27. https://doi.org/https://doi.org/10.1016/j.eswa.2019.02.002

Brown, R., Hanson, A., Willis, H., Luedtke, F., & Born, M. (2001). Assessing the reliability of distribution systems. *IEEE Computer Applications in Power*, *14*(1), 44–49. https://doi.org/10.1109/67.893355

D., Q., J., M., B., C., E., J., & Sousa Santos, V. (2017). Recent trends of the most used metaheuristic techniques for distribution network reconfiguration. *Journal of Engineering Science and Technology Review*.

Duan, D. L., Ling, X. D., Wu, X. Y., & Zhong, B. (2015). Reconfiguration of distribution network for loss reduction and reliability improvement based on an enhanced genetic algorithm. *International Journal of Electrical Power & Energy Systems*, *64*, 88–95. https://doi.org/https://doi.org/10.1016/j.ijepes.2014.07.036

Eldurssi, A. M., & O'Connell, R. M. (2015). A fast non-dominated sorting guided genetic algorithm for multi-objective power distribution system reconfiguration problem. *IEEE Transactions on Power Systems*, *30*(2), 593–601. https://doi.org/10.1109/TPWRS.2014.2332953

Gallego Pareja, L. A., López-Lezama, J. M., & Gómez Carmona, O. (2023). Optimal feeder reconfiguration and placement of voltage regulators in electrical distribution networks using a linear mathematical model. *Sustainability*, *15*(1). https://doi.org/10.3390/su15010854

Ganesh, S., & Kanimozhi, R. (2018). Meta-heuristic technique for network reconfiguration in distribution system with photovoltaic and d-statcom. *IET Generation, Transmission & Distribution*, *12*(20), 4524–4535.

Gupta, N., Swarnkar, A., Niazi, K., & Bansal, R. (2010). Multi-objective reconfiguration of distribution systems using adaptive genetic algorithm in fuzzy framework. *IET Generation, Transmission & Distribution*, *4*, 1288–1298. https://doi.org/10.1049/iet-gtd.2010.0056

Gupta, N., Swarnkar, A., & Niazi, K. (2014). Distribution network reconfiguration for power quality and reliability improvement using genetic algorithms. *International Journal of Electrical Power & Energy Systems*, *54*, 664–671. https://doi.org/https://doi.org/10.1016/j.ijepes.2013.08.016

Helmi, A. M., Carli, R., Dotoli, M., & Ramadan, H. S. (2021). Efficient and sustainable reconfiguration of distribution networks via metaheuristic optimization. *IEEE Transactions on Automation Science and Engineering*, *19*(1), 82–98.

Hernández Valencia, J., López-Lezama, J., & Restrepo Cuestas, B. (2021). Assessing the vulnerability of power systems using multilevel programming: A literature review. *Revista Ingenierías Universidad De Medellín*, *20*. https://doi.org/10.22395/rium.v20n38a6

Huang, Y. (2002). Enhanced-genetic-algorithm-based fuzzy multi-objective approach to distribution network reconfiguration. *IEE Proceedings-Generation, Transmission and Distribution*, *149*(5), 615–620.

Kahouli, O., Alsaif, H., Bouteraa, Y., N., B. A., & Chaabene, M. (2021). Power system reconfiguration in distribution network for improving reliability using genetic algorithm and particle swarm optimization. *Applied Sciences*, *11*(7), 3092.

McCall, J. (2005). Genetic algorithms for modelling and optimisation. *Journal of Computational and Applied*

Mathematics, *184*(1), 205–222. https://doi.org/https://doi.org/10.1016/j.cam.2004.07.034

Naik, S., Khatod, D., & Sharma, M. (2013). Optimal allocation of combined dg and capacitor for real power loss minimization in distribution networks. *International Journal of Electrical Power & Energy Systems*, *53*, 967–973. https://doi.org/https://doi.org/10.1016/j.ijepes.2013.06.008

Razavi, S.-M., Momeni, H.-R., Haghifam, M.-R., & Bolouki, S. (2022). Multi-objective optimization of distribution networks via daily reconfiguration. *IEEE Transactions on Power Delivery*, *37*(2), 775–785. https://doi.org/10.1109/TPWRD.2021.3070796

Salau, A. O., Gebru, Y. W., & Bitew, D. (2020). Optimal network reconfiguration for power loss minimization and voltage profile enhancement in distribution systems. *Heliyon*, *6*(6), e04233. https://doi.org/https://doi.org/10.1016/j.heliyon.2020.e04233

Stojanović, I., Brajević, I., Stanimirović, P. S., Kazakovtsev, L. A., Zdravev, Z., et al. (2017). Application of heuristic and metaheuristic algorithms in solving constrained weber problem with feasible region bounded by arcs. *Mathematical Problems in Engineering*, *2017*.

Swarnkar, A., Gupta, N., & Niazi, K. (2011). A novel codification for meta-heuristic techniques used in distribution network reconfiguration. *Electric Power Systems Research*, *81*(7), 1619–1626.

Zhang, J., Yuan, X., & Yuan, Y. (2014). A novel genetic algorithm based on all spanning trees of undirected graph for distribution network reconfiguration. *Journal of Modern Power Systems and Clean Energy*, *2*, 143–149. https://doi.org/https://doi.org/10.1007/s40565-014-0056-0

Zhu, J. (2002). Optimal reconfiguration of electrical distribution network using the refined genetic algorithm. *Electric Power Systems Research*, *62*(1), 37–42. https://doi.org/https://doi.org/10.1016/S0378-7796(02)00041-X