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Revenue loss reduction in electrical distribution networks using distributed generators: A case of Tanzania electrical distribution network

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Abstract

Most power losses in power systems occur in distribution networks, leading to poor service quality, higher electricity costs, and utility revenue losses. This study addresses these challenges by integrating distributed generators (DGs) into distribution networks to minimize revenue losses. The proposed strategy involves determining optimal DG power output at fixed locations, making it a complex NP-hard optimization due to fluctuating system variables. This study involves metaheuristic algorithms to solve the DG power dispatch problem in order to reduce revenue losses. The proposed technique has been tested in the Tanzanian electrical distribution network using an hourly load profile and tariff D1, T1 and T2 users. Four metaheuristic algorithms, namely Golden jackal optimization (GJO), Grey wolf optimizer (GWO), Walrus optimizer (WO), and Marine Predators Algorithm (MPA) were evaluated. The performance of the algorithms was assessed through convergence profiles and computational times, with GWO emerging as the most effective. The findings reveal that increasing the number of DGs reduces revenue losses, while tariff category analysis shows an average loss reduction of over 56% across all cases. These results highlight the effectiveness of DG integration in minimizing revenue losses and improving the efficiency of electrical distribution networks.

Keywords

Meta-heuristic Algorithms
DG Allocation
Radial Distribution Network
Revenue loss
Power loss

1. Introduction

An electrical power system is a complex network that encompasses electric power generation, transmission, and distribution. It is designed to deliver electricity from power plants to consumers efficiently and reliably. The distribution network is the part of the electrical power system that delivers the electrical power to the end users [1]. The distribution part of the network is further subdivided into the primary distribution network, which comprises the 11kV and 33kV lines, and the secondary distribution network, which comprises the LV transformers and 400V/230V lines. Due to its direct correlation with customers and its impact on electricity cost and power supply reliability, the secondary distribution network continues to be one of the most important topics in the electric power industry [2].

The secondary distribution network is dynamic, the most complex part of the power system, and its management is very challenging. The most challenging issue in the secondary distribution network is the technical and non-technical power losses [3]. Technical losses occur naturally during the transmission and distribution of electricity, primarily due to resistance in conductors and transformer inefficiencies. Conversely, non-technical losses often arise from issues such as power theft, fraud, meter inaccuracies, non-payment, and billing irregularities [4]. Non-technical loss of electricity is a significant issue, particularly in developing countries, and represents a substantial financial burden on utility companies, governments, and society. According to recent studies, these losses can account for a considerable percentage of total electricity distributed, leading to significant revenue shortfalls [5].

Technical losses are quite challenging in developing countries with relatively poor and aged infrastructure. In secondary distribution network (SDN) and distribution transformer, no-load losses contribute 53-74% of the total technical losses in the power system [6]. These losses not only affect the financial viability of energy providers but also hinder efforts to expand access to electricity, particularly in underserved regions. The losses cause a significant increase in operational costs, making the electrical charges comparatively high to compensate for the losses.

In Tanzania, electricity charges are proposed by Tanzania Electric Supply Company Limited (TANESCO), the main utility company responsible for generating, transmitting, and supplying electricity. The prices are categorized into tariff groups, including tariff D1, T1, T2, T3-MV, and T3-HV. Most customers in the electrical secondary distribution networks use tariffs D1, T1, and T2. The proposed prices are implemented after getting approval from the Energy and Water Utilities Regulatory Authority (EWURA), the authority responsible for regulating energy and water prices in Tanzania. For example, in January 2016, EWURA approved the request from TANESCO to increase tariff rates by about 8.53% in Tanzania. This increase was aimed at enabling TANESCO to cover operational costs and support ongoing modernization projects while balancing affordability for consumers [7].

TANESCO has ongoing efforts and initiatives to reduce revenue losses and improve service delivery in Tanzania. TANESCO has made progress in reducing system losses, reporting a decline from 23% in 2010 to 18% by the end of 2014 as part of its continuous efforts to enhance power delivery efficiency [8]. The effort to reduce the revenue loss has recently realized significant output, where the state power firm has been able to reduce losses from 21% in 2018 to 14% in 2024, just 5% short of the global benchmark of 9% electricity loss [9]. Such achievement has been possible due to infrastructure upgrades and increasing generation capacity. Despite such efforts and initiatives, power losses remain a challenging issue, and utility companies in Tanzania and most developing countries need immediate intervention.

Integrating distributed generators (DGs) in power systems presents a promising solution to mitigate these losses [10]. Distributed generation refers to small-scale power generation technologies, such as solar panels and wind turbines, which can be deployed close to the point of consumption [11]. By decentralizing power production, DGs can reduce the distance electricity must travel through the grid, thereby minimizing technical losses. Furthermore, DGs can enhance grid reliability and resilience by providing local power sources during peak demand periods or outages [12]. Introducing DGs in the electrical distribution networks involves locating optimal places for DGs and optimal power dispatched by each DG depending on changing power system variables, which makes the whole process an NP-hard optimization problem [13]. Three methods are available for DG placement: analytical methods, numerical methods, and metaheuristic algorithms. Metaheuristic algorithms are the most popular method for solving DG placement problems because they can find near-optimal solutions for large and complex optimization problems [14]. Therefore, this study proposes using metaheuristic algorithms to solve DG's power dispatch problem and reduce revenue losses in electrical distribution networks. The fixed locations of the DG were considered, and the optimal size for each DG was found using metaheuristic algorithms. Unlike other studies that considered loss as the objective function, this study formulated the objective function of electricity revenue losses.

The mathematical model formulated in this study incorporates power system variables and electricity price tariffs, focusing on three tariff categories in Tanzania: D1, T1, and T2, which are applicable to most users in the country's secondary distribution networks. Four metaheuristic algorithms, namely Golden jackal optimization (GJO) [15], Grey wolf optimizer (GWO) [16], Walrus optimizer (WO) [17], and Marine Predators Algorithm (MPA) [18], were compared and used to find optimal DG settings that minimize revenue loss in Tanzania's electrical distribution networks. The algorithms were evaluated based on convergence profiles and computational times, with GWO performing the best. The study also focuses on analyzing the impact of different tariffs and the number of DGs on revenue loss reduction to determine the overall revenue loss reductions

2. Method

2.1 Tanzania Power Systems

The electrical distribution network comprises 33kV, 11kV, and 0.4kV lines. The 2021/2022 report shows that TANESCO distribution network comprises approximately 148,544 km of distribution lines, which includes 8,325 km of 33kV lines, 3,732 km of 11kV lines, and 12,992 km of lower voltage lines [19]. As of June 2022, TANESCO had connected about 3.79 million customers, representing a 17% increase of the customer base from the previous year [8]. The electrical distribution network is essential since it interconnects the transmission system and the users [20]. The distribution system consists of the most extensive coverage and is widely scattered. The nature of the secondary distribution network is complicated, and most households are in un-surveyed areas, making the situation more complex [21].

2.2 Electricity Prices in Tanzania

TANESCO sets its electricity pricing structure to reflect its efforts to balance affordability for consumers while ensuring sustainability. Table 1 presents the categories of the approved power tariff in Tanzania [7].

Table 1. Electricity tariffs and prices in Tanzania [7].

Tariff	Description	Unit Price (TZS)
D1	Domestic Low Usage, for low consumption users (using an average greater than 75 kWh per Month)	350
T1	General Usage Tariff for customers includes residential, small commercial, light industrial use, public lighting, and billboards. Power is supplied at low voltage single phase (230V) as well as three-phase (400V).	292
T2	Low Voltage Maximum Demand Usage, for general use at 400 Volts with average consumption greater than 7500 kWh per meter reading period and demand does not exceed 500kVA per meter reading period	195
T3-MV	Applicable customers connected to Medium Voltage Maximum Demand Usage or general use where power is metered at 11/33 kV	157
T3- HV	Applicable to customers connected to High Voltage in, including ZECO hulu , and Twiga Cement	152

2.3 The Electrical Network of the Study Area

The study area for this work was selected from part of the Tanzania electrical SDN. This area comprises customers with different tariffs (D1, T1, T2, and T3) and is easily accessible. The specific regions selected were in the Kinondoni North Area near Msasani Peninsula Hospital. The selected area has 79 nodes with 143 customers connected with different tariff plans. The customers connected to this network use D1, T1, and T2 tariff schemes. Hence, this study focuses on D1, T1, and T2 customers whose information was available in the selected area. Figure 1 presents the electrical network topology of the study area. The root node is considered the node with the transformer. The optimal DG places are the locations of DGs considered in this study, nodes 90, 111, 125, and 145.

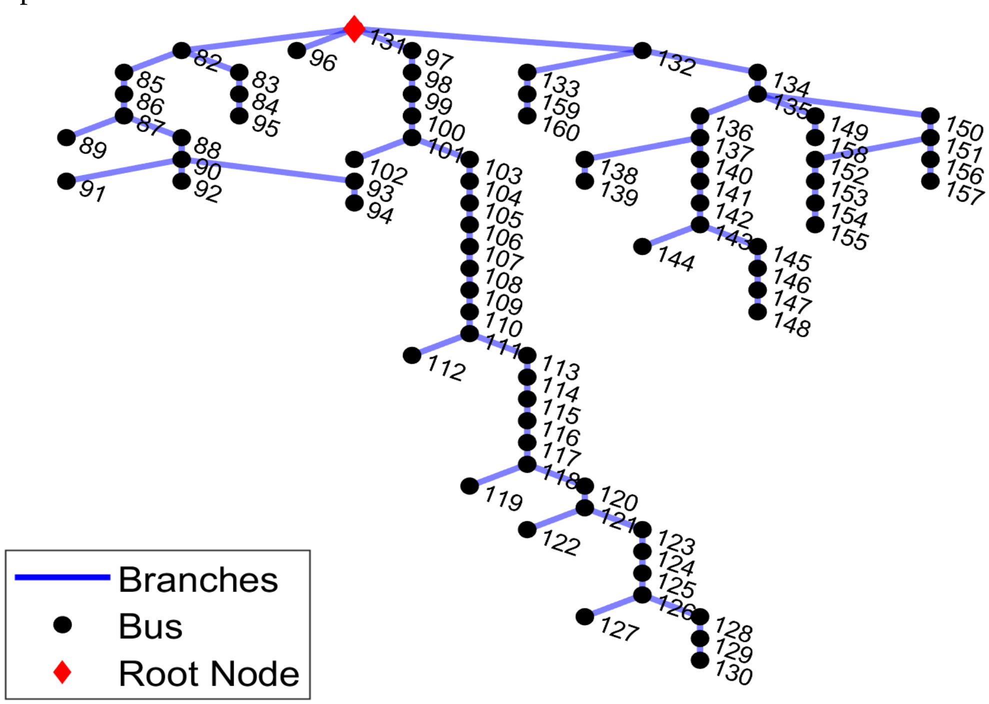

Figure 1. Study area electrical network topology [22].

2.4 The Daily Load Profile of the Study Area

The study area is served by the transformer, which collects data using the Automatic Meter Reader (AMR) system in 20-minute resolution. The electricity consumption records for seven years, from 2012 to 2019, were used. The AMR data was converted into an hourly resolution to align with the purpose of the study, which requires calculating electricity consumption units. From the processed hourly data, the maximum and average load profiles for each hour were calculated (Figure 2).

The maximum load values were used in this study. Since the available data were the aggregated data for all nodes served by the transformer, it was necessary to disaggregate them in order to get the power consumption for each node. Each hourly value was divided by the number of nodes by assigning a random weight in order to capture the load's stability and randomness.

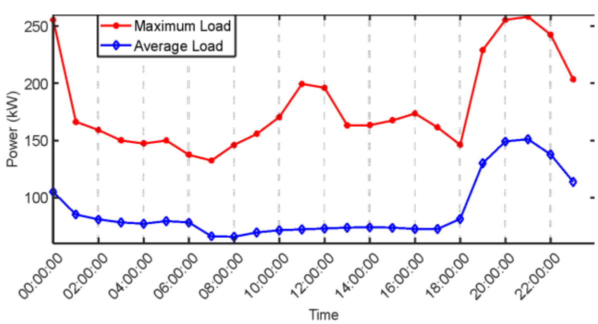

Figure 2. The Maximum and average hourly load.

2.4.1 Objective functions

Customers with Tariff D1, T1, and T2 can be connected to the electrical secondary distribution networks. Based on the above assumptions, the hourly revenue loss for the electrical distribution network can be presented as

$$Y = T_a \sum_{a=1}^{N_a} (I_a)^2 R_a + T_b \sum_{b=1}^{N_b} (I_b)^2 R_b + T_c \sum_{c=1}^{N_c} (I_c)^2 R_c, \quad (1)$$

where Y is the total revenue loss of the distribution network, $N_a + N_b + N_c = N$, N is the total number of buses, N_a is the total number of D1 buses, N_b is the total number of T1 buses, and N_c is the total number of T2 buses. T_a is the unit price of electricity for D1 users, T_b is the unit price of electricity for T1 users, and T_c is the unit price of electricity for T2 users. I_a is the current flowing in the upstream branch of the D1 bus, I_b is the current flowing in the upstream branch of the T1 bus, and I_c is the current flowing in the upstream branch of the T2 bus. R_a, R_b and R_c are the resistances of the upstream branch for D1, T1 and T2 buses, respectively.

2.4.2 Constraints

When operating DGs, the objective function is subjected to the constraint presented in equations (2) to (6).

A. Power balance constraints

$$P_{DG} = P_{loss} + P_D, \quad Q_{DG} = Q_{loss} + Q_D \quad (2)$$

P_{DG} and Q_{DG} are the total active and reactive power injected by the DGs, respectively. P_{DG} and Q_D are the active and reactive power of the load at the i^{th} bus, respectively. P_{loss} is the total active power loss of the network given by (3), and Q_{loss} is the total reactive power loss of the network given by (4).

$$P_{loss} = \sum_{i=1}^{N} (I_i)^2 R_i \quad (3)$$

$$Q_{loss} = \sum_{i=1}^{N} (I_i)^2 X_i \quad (4)$$

Where I_i is the current through the branch i, R_i is the resistance of branch i, and X_i is the reactance of branch i, and N is the total number of branches in the network.

B. Voltage constraints

$V_{min} < V_i < V_{max}$ where $i = 1,2,3, \ldots, n$.

Where V_i is the voltage magnitude at i^{th} bus. V_{min} is the lower voltage limits and V_{max} is the upper voltage limit for a power system. In this work, the lower and upper voltage limits were set at 0.9 p.u and 1.1 p.u, respectively. The values of voltage limits are according to the Tanzania electrical power system and the approach by Kawambwa et al. [14].

C. DG active and reactive power constraints

$$P_{i,min}^{DG} < P_i^{DG} < P_{i,max}^{DG} \tag{5}$$

$$Q_{i,min}^{DG} < Q_i^{DG} < Q_{i,max}^{DG} \tag{6}$$

Where $P_{i,min}^{DG}$ is the lower active power limit of DG, $Q_{i,min}^{DG}$ is the lower reactive power limit of DG, $P_{i,max}^{DG}$ is the upper active power limit of DG, and $Q_{i,max}^{DG}$ is the upper reactive power limit of DG. P_i^{DG} and Q_i^{DG} are active and reactive power of the DGs at i^{th} bus, respectively.

2.5 Metaheuristic Algorithm for Revenue Loss Reduction

Metaheuristic algorithms are powerful optimization techniques designed to address complex, non-deterministic, and non-linear problems frequently encountered in engineering, computer science, and operations research [23]. Metaheuristic algorithms have found extensive applications in power systems, where they are used for various applications, such as optimal power flow, power dispatch, economic load dispatch, and microgrid management [24]. Among these applications, distributed generator (DG) placement stands out as a particularly complex optimization challenge. This task involves determining the optimal sizes and locations for DGs within power systems while adhering to specific objective functions and constraints [25]. Given the dynamic nature of power systems, the intermittency of DGs, and fluctuating operating conditions, achieving optimal placement becomes a highly complex work. Several metaheuristic algorithms have been used to solve DG placement problems: Symbiotic Organism Search [26], Particle Swarm Optimization [27], Golden jackal optimization (GJO) [15], Grey wolf optimizer (GWO) [16], Walrus optimizer (WO) [17], Marine Predators Algorithm (MPA) and Chimp Optimization Algorithm[28]. Despite the differences in the structure of metaheuristic algorithms, some steps for their implementation for placement and sizing are common.

This study explores the four metaheuristic algorithms GJO, GWO, WO, and MPA to determine the best algorithm that can be used for further analysis of the electrical losses. The four algorithms were chosen due to their prominence in solving DG placement problems.

This study explores the role of distributed generation (DG) in mitigating revenue losses for power utility companies. The study assumes the DGs are available and optimally placed. Metaheuristic algorithms are employed to determine the ideal DG sizes while accounting for fluctuating load demands over time. Such assumptions reduce the dimensions and complexity of the problem. Figure 3 illustrates a flowchart to implement metaheuristic algorithms for sizing DGs within the power system.

Metaheuristic algorithms are population-based, where each possible solution is treated as a member of a population. In this study, these population members represent possible sizes for each DG location. Factors such as the number of distributed generators (DGs), population size, load data, line data, and tariff information are set during initialization. The power tariff information involves electricity prices for each user category.

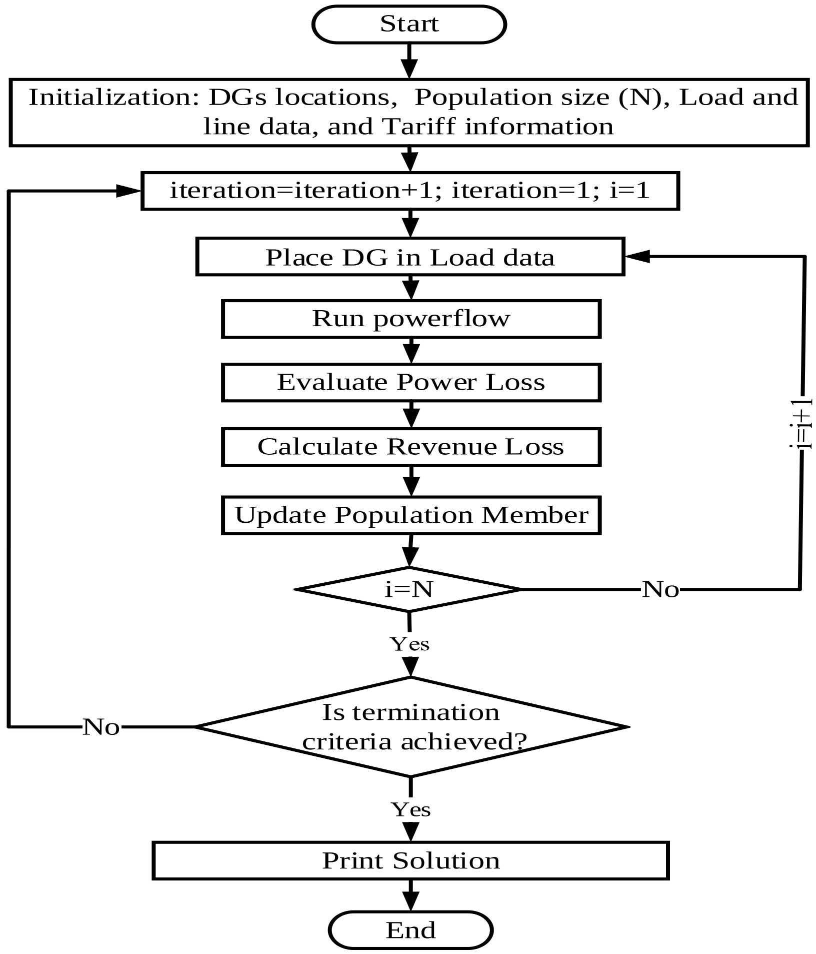

Figure 3. Implementation of metaheuristic algorithms for optimal sizing of DGs in a power system.

The power flow results are combined with power loss and tariff information when calculating revenue loss according to equation (1). The load data are changed by placing the DG sizes in particular locations before running the power flow. Then, the population member is updated according to the member update mechanisms of the metaheuristic algorithm. All members of metaheuristic algorithms are updated accordingly. The algorithm terminates when the criteria are met, or a number of iterations have been reached.

3. Results and Discussions

This study compares four metaheuristic algorithms for reducing revenue loss in an electrical distribution network using distributed generators (DGs), with the Tanzanian electrical distribution network serving as a case study. Two cases were analyzed: the first involved placing 2 DGs at buses 90 and 111, and the second involved placing 4 DGs at buses 90, 111, 125, and 145, following the approach of Kawambwa and Mnyanghwalo [22]. The study did not focus on finding optimal DG locations but on finding the DG sizes at the known locations.

3.1 Parameter Settings for Metaheuristic Algorithms

In this study, four metaheuristic algorithms were considered: Golden jackal optimization (GJO) [15], Grey wolf optimizer (GWO) [16], Walrus optimizer (WO) [17], and Marine Predators Algorithm (MPA) [18]. Metaheuristic algorithms differ in mathematical formulation and implementation structure. The control parameters for the considered metaheuristic algorithms are presented in Table 2. The control parameters of each algorithm were taken from the original article of the corresponding algorithm [15-18]. All algorithms incorporated 30 population members running for 200 iterations. All Simulations were carried out using MATLAB 2021b on a 3.80 GHz, 4 Cores i7 computer with 16 GB RAM.

Table 2: Parameter settings of metaheuristic algorithms.

SN	Algorithm	Parameters
1	GJO [15]	$c_1 = 1.5$
2	GWO [16]	a=2 to 0 (linearly)
3	WO[17]	Proportion of females (P)=0.4
4	MPA [18]	FADS = 0.2

3.2 Results for Convergence and Execution Time of the Metaheuristic Algorithms

The performance of the four metaheuristic algorithms in reducing revenue loss using DGs was evaluated based on convergence profiles and computational times. The convergence trends for Cases 1 and 2 were similar, so only Case 2 with tariff D1 is shown in Figure 4. Table 3 presents the average execution times of the algorithms over 20 independent runs for the two cases and the three considered tariffs (D1, T1, and T2).

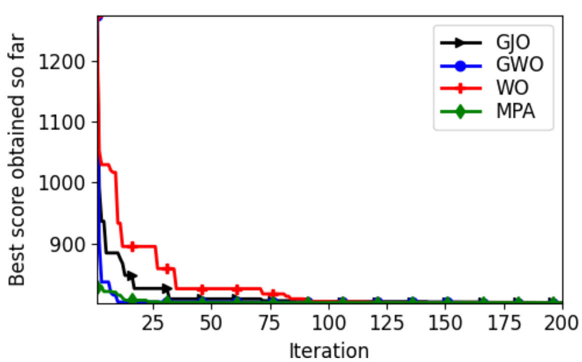

Figure 4. Algorithms' convergence profiles.

Considering the representative convergence profile in Figure 2, for all cases the MPA and GWO were the fastest. The GWO was the fastest since it could find the globally optimal values faster than other algorithms, followed by the GJO, and the WO was the slowest in achieving global optimal value.

Considering the execution time for all Tariffs and all algorithms, the execution time for case 2 is greater than case 1 because case 2 involves four DGs, and case 1 involves 2 DGs. Therefore, case 2 has higher dimensional solution space than case 1. Comparing the algorithms for all scenarios, the GJO has been the best for scenarios 2, 5, and 6, and GWO has been the best for scenarios 1,3 and 4. Considering the average execution time, the GJO was the best, followed by GWO and WO. The MPA has the worst computational efficiency.

When considering the convergence profile, the best performers are the GWO and MPA; however, the MPA is the most computationally intensive. When considering the execution time, the best performers are the GJO and GWO; however, the convergence characteristics of the GWO surpass the GJO. Therefore, the best choice is the GWO. In this study, whenever the results for one algorithm needed to be presented, the results of the GWO were considered.

3.3 Results for Revenue Loss Reduction Using Distributed Generators

Experiments were conducted to examine the impact of distributed generators (DGs) on reducing revenue losses in an electrical distribution network. Revenue loss was calculated for three scenarios: without DGs, with two DGs, and with four DGs. Four tariff cases were analyzed: Case 1 involved D1 users, Case 2 involved T1 users, Case 3 involved T2 users, and Case 4 included a mix of T1 and D1 users. In Case 4, out of 78 nodes, 30 were T1 users, and the remaining were D1, with the nodes for T1 and D1 selected arbitrarily.

Table 3: Execution time of the algorithms (in Seconds).

	D1		T1		T2		
	Case 1 (Scenario 1)	Case 2 (Scenario 2)	Case 1 (Scenario 3)	Case 2 (Scenario 4)	Case 1 (Scenario 5)	Case 2 (Scenario 6)	Average
GJO	355.386	400.099	491.894	502.018	389.043	409.562	424.667
GWO	353.237	402.455	468.462	498.460	409.672	420.030	425.386
WO	356.850	412.594	503.736	527.388	404.033	415.838	436.740
MPA	726.105	814.346	964.358	981.658	806.419	832.862	854.291

The experiments were performed using all algorithms and tariff cases, but the results for the GWO algorithm were emphasized due to the reasons outlined in Section 3.2. Figure 5 shows the hourly revenue loss for tariff Case 1 (D1), Figure 6 illustrates the hourly revenue loss for tariff Case 2 (T1), Figure 7 presents the hourly revenue loss for tariff Case 3 (T2), and Figure 8 displays the hourly revenue loss for tariff Case 4 (a combination of T1 and D1 users).

The results indicate that revenue loss is higher when no DGs are present than when DGs are used across all cases. Additionally, the results with 4 DGs outperform those with 2 DGs, demonstrating that revenue loss decreases as the number of DGs increases. However, as shown in Table 3, this improvement comes with the trade-off of increased computational effort, as execution time rises with the number of DGs.

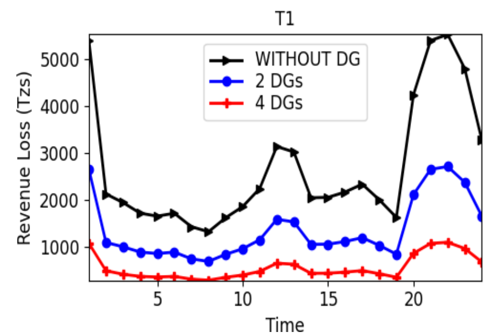

Figure 6. Revenue loss for T1.

Table 4 summarizes the results of revenue loss reduction, showing that in all tariff cases, the percentage of revenue loss reduction is more significant with 4 DGs compared to 2 DGs. The percentage of revenue loss reduction was calculated according to equation (7). In every case, placing 4 DGs reduces revenue loss by over 63%. Overall, the combined results demonstrate an average loss reduction of 56.49% across all tested cases.

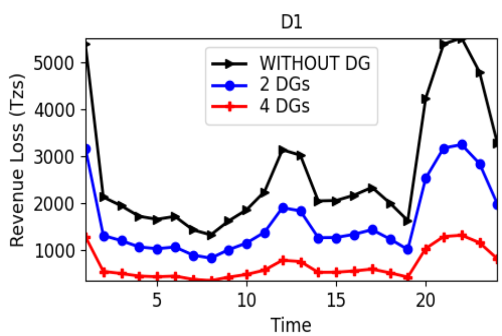

Figure 5. Revenue loss for D1.

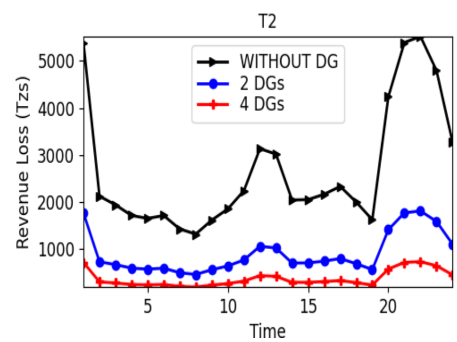

Figure 7. Revenue loss for T2.

Table 4. Revenue loss reduction.

	D1		T1		T2		
	2 DGs	4 DGs	2 DGs	4 DGs	2 DGs	4 DGs	Average
Without DG (Tzs)	43084	43084	64516	64516	43084	43084	50228
With DG (Tzs)	38962	15858	32506	13269	21708	8835	21856
Reduction (%)	9.57	63.19	49.62	79.43	49.62	79.49	56.49

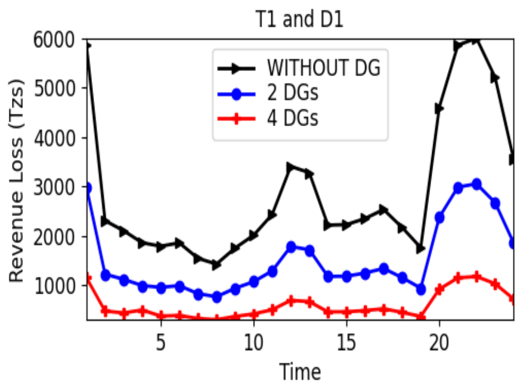

Figure 8. Revenue loss for T1 and D1.

$$Reduction = \frac{LOSS_{no\ DG} - LOSS_{with\ DG}}{LOSS_{no\ DG}} \times 100\% \quad (7)$$

Where $LOSS_{no\ DG}$ is the revenue loss without DGs and $LOSS_{with\ DG}$ is the revenue loss when the DGs are placed.

This study uses metaheuristic algorithms to determine the optimal DG settings in response to varying power system parameters. As the system load fluctuates hourly based on user consumption, the algorithms adjust to find the best DG configurations. Figure 6 presents the results for DG settings across each hour, considering the placement of 4 DGs. The results demonstrate that the optimal power output of the DGs changes in line with the load profile variations, proving the effectiveness of metaheuristic algorithms.

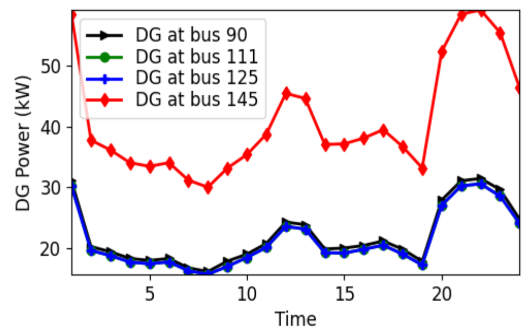

Figure 9. Hourly DG settings.

4. Conclusion and Recommendations

This study explores the use of distributed generators (DGs) to reduce revenue losses in electrical distribution networks, with the objective function based on electricity tariff data from Tanzania, specifically the D1, T1, and T2 tariffs. The DG placement scenarios included 2 and 4 DGs, and metaheuristic algorithms were employed to find the optimal DG settings in response to fluctuating power system loads. Four algorithms were compared, namely GJO, GWO, WO, and MPA, with GWO performing best regarding convergence profile and computational time. The results show that DGs reduced revenue losses by an average of over 56% in all cases, with higher reductions recorded as the number of DGs increased. The value is higher, as with the increased number of generators, the electrical line distance from the source to the load was highly shortened, hence a reduced drop, which resulted in reduced revenue losses. Furthermore, the considered network section had low coverage; therefore, its loss reduction impacts on DG incorporation are highly realized to prove the concept. Thus, the study concludes that incorporating DGs into electrical distribution networks effectively reduces revenue losses.

In this study, revenue loss was calculated based on power losses due to current flow in the network branches. Other factors contributing to power losses, such as electricity theft, could also be incorporated into the mathematical formulation. The results indicate that revenue loss decreases as the number of DGs increases, though the costs of DG installation were not considered. Future research may explore the inclusion of DG installation costs to provide a more comprehensive analysis. The DG integration in the electrical distribution networks requires the power system infrastructure to support two-way power flow. However, the existing practical Tanzania power distribution network was designed for one-way power flow. In order to reap the advantages offered by the DGs in the Tanzanian power distribution system, as elaborated in this study, network upgrading is required. The approaches used in this study are generic and can be used anywhere so long as the usage tariffs are the same. In case there are differences in tariffs, minor adjustments should be made to reflect the specific tariff prices.

CONTRIBUTIONS OF CO-AUTHORS

Shamte Kawambwa	[ORCID: 0000-0003-1937-8727]	Conceived the idea, conducted experiments and wrote the paper
Daudi Mnyanghwalo	[ORCID: 0000-0003-0476-4860]	Wrote the paper and analyzed the results

REFERENCES

[1] G. Mokryani, "Distribution Network Types and Configurations," in *Future Distribution Networks: Planning, Operation, and Control*. Melville, New York: AIP Publishing LLC, 2022, ch. 1, pp. 1-18.

[2] R. E. Brown, *Electric power distribution reliability*, 2nd ed. (Power Engineering Willis). Boca Raton, FL, USA: CRC press, 2017, p. 504.

[3] H. Henriques, R. Corrêa, M. Fortes, B. Borba, and V. Ferreira, "Monitoring technical losses to improve non-technical losses estimation and detection in LV distribution systems," *Measurement*, vol. 161, p. 107840, 2020, doi: 10.1016/j.measurement.2020.107840.

[4] M. A. Souza *et al.*, "Detection of Non-Technical Losses on a Smart Distribution Grid Based on Artificial Intelligence Models," *Energies*, vol. 17, no. 7, p. 1729, 2024, doi: 10.3390/en17071729.

[5] H. Firoozi and H. R. Mashhadi, "Non-technical loss detection in limited-data low-voltage distribution feeders," *International Journal of Electrical Power & Energy Systems*, vol. 135, p. 107523, 2022, doi: 10.1016/j.ijepes.2021.107523.

[6] G. Strbac, P. Djapic, D. Pudjianto, I. Konstantelos, and R. Moreira, "Strategies for reducing losses in distribution networks," *Imperial College, UK Power Networks, London, UK*, Technical Report pp. 1-87, 2018.

[7] EWURA, "In the matter of Application by the tanzania electric supply company limited For Tariff Review Application," Energy and Water Utilities Regulatory Authority (EWURA), 2016. Accessed: 27/09/2024. [Online]. Available: https://www.ewura.go.tz/wp-content/uploads/2019/03/TANESCO-Tariff-Adjustment-Order-2016-GN.-119-2016.pdf.

[8] TANESCO, "Annual report 2021/2022," Tanzania Electric Supply Company Limited (TENESCO), 2022. Accessed: 27/09/2024. [Online]. Available: https://www.tanesco.co.tz/attachments/media/publications/ugBmdTXeD8_Ag8sTDp2KXtrlYjHtA8RM_Annual%20Report%202021_22_2023_07_30_07_17_07.pdf.

[9] D. Minja. (2024, 06 November 2024) TANESCO cuts electricity losses to 14pc. *dailynews*. Available: https://dailynews.co.tz/tanesco-cuts-electricity-losses-to-14pc/

[10] R. Ufa, Y. Y. Malkova, V. Rudnik, M. Andreev, and V. Borisov, "A review on distributed generation impacts on electric power system," *International journal of hydrogen energy*, vol. 47, no. 47, pp. 20347-20361, 2022, doi: 10.1016/j.ijhydene.2022.04.142.

[11] M. Belrzaeg, M. Abou Sif, E. Almabsout, and U. A. Benisheikh, "Distributed generation for Microgrid technology," *International Journal of Scientific Research Updates*, vol. 6, no. 1, pp. 083-092, 2023, doi: 10.53430/ijsru.2023.6.1.0062.

[12] V. Khare and P. Chaturvedi, "Design, control, reliability, economic and energy management of microgrid: A review," *e-Prime-Advances in Electrical Engineering, Electronics and Energy*, vol. 5, no. 100239, 2023, doi: 10.1016/j.prime.2023.100239.

[13] K. Subbaramaiah and P. Sujatha, "Optimal DG unit placement in distribution networks by multi-objective whale optimization algorithm & its techno-economic analysis," *Electric Power Systems Research*, vol. 214, no. Part A, p. 108869, 2023, doi: 10.1016/j.epsr.2022.108869.

[14] S. Kawambwa, R. Mwifunyi, D. Mnyanghwalo, N. Hamisi, E. Kalinga, and N. Mvungi, "An improved backward/forward sweep power flow method based on network tree depth for radial distribution systems," *Journal of Electrical Systems Information Technology,* vol. 8, no. 1, pp. 1-18, 2021, doi: 10.1186/s43067-021-00031-0.

[15] N. Chopra and M. M. Ansari, "Golden jackal optimization: A novel nature-inspired optimizer for engineering applications," *Expert Systems with Applications*, vol. 198, p. 116924, 2022, doi: 10.1016/j.eswa.2022.116924.

[16] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Advances in engineering software*, vol. 69, pp. 46-61, 2014, doi: 10.1016/j.advengsoft.2013.12.007.

[17] M. Han, Z. Du, K. F. Yuen, H. Zhu, Y. Li, and Q. Yuan, "Walrus optimizer: A novel nature-inspired metaheuristic algorithm," *Expert Systems with Applications,* vol. 239, p. 122413, 2024, doi: 10.1016/j.eswa.2023.122413.

[18] A. Faramarzi, M. Heidarinejad, S. Mirjalili, and A. H. Gandomi, "Marine Predators Algorithm: A nature-inspired metaheuristic," *Expert systems with applications*, vol. 152, p. 113377, 2020, doi: 10.1016/j.eswa.2023.122413.

[19] I. ICH. (2021, 03 September 2021) Tanzania Electric Supply Company Ltd (TANESCO). Available: https://ich.no/tanzania-electric-supply-company-ltd-tanesco/.

[20] S. Pinzón, S. Yánez, and M. Ruiz, "Optimal location of transformers in electrical distribution networks using geographic information systems," *Enfoque Ute,* vol. 11, no. 1, pp. 84-95, 2020, doi: 10.29019/enfoque.v11n1.593.

[21] Z. Wang, X. Shen, H. Sun, and Q. Wu, "A Practical Urban Distribution Network Planning Method With Geographic Information System," *IEEE Transactions on Power Systems,* vol. 39, no. 6, pp. 7038-7049, 2024, doi: 10.1109/TPWRS.2024.3384534.

[22] S. Kawambwa and D. Mnyanghwalo, "A multi-agent-based symbiotic organism search algorithm for DG coordination in electrical distribution networks," *Journal of Electrical Systems and Information Technology,* vol. 10, no. 1, pp. 1-19, 2023, doi: 10.1186/s43067-023-00072-7.

[23] S. M. Almufti, A. A. Shaban, Z. A. Ali, R. I. Ali, and J. A. D. Fuente, "Overview of metaheuristic algorithms," *Polaris Global Journal of Scholarly Research and Trends,* vol. 2, no. 2, pp. 10-32, 2023, doi: 10.58429/pgjsrt.v2n2a144.

[24] A. M. Nassef, M. A. Abdelkareem, H. M. Maghrabie, and A. Baroutaji, "Review of metaheuristic optimization algorithms for power systems problems," *Sustainability,* vol. 15, no. 12, p. 9434, 2023, doi: 10.3390/su15129434.

[25] D. Nageswari, N. Kalaiarasi, and G. Geethamahalakshmi, "Optimal Placement and Sizing of Distributed Generation Using Metaheuristic Algorithm," *Comput. Syst. Sci. Eng.,* vol. 41, no. 2, pp. 493-509, 2022, doi: 10.32604/csse.2022.020539.

[26] S. Kawambwa, N. Hamisi, P. Mafole, and H. Kundaeli, "A cloud model based symbiotic organism search algorithm for DG allocation in radial distribution network," *Evolutionary Intelligence,* vol. 15, no. 1, pp. 545-562, 2022, doi: 10.1007/s12065-020-00529-y.

[27] E. M. Sayed, N. H. Elamary, and R. A. Swief, "Optimal sizing and placement of distributed generation (DG) using particle swarm optimization," in *6th International conference on Advanced Technology and Applied Sciences (ICaTAS 2021)*, Cairo, Egypt, 2021, vol. 2128, no. 1: Journal of Physics: Conference Series pp. 12-23, doi: 10.1088/1742-6596/2128/1/012023.

[28] A. Fathy, D. Yousri, A. Y. Abdelaziz, and H. S. Ramadan, "Robust approach based chimp optimization algorithm for minimizing power loss of electrical distribution networks via allocating distributed generators," *Sustainable Energy Technologies and Assessments*, vol. 47, p. 101359, 2021, doi: 10.1016/j.seta.2021.101359.