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Reconfiguration of Distribution Networks using a Genetic Algorithm with Rank-Weight Selection and Constrains

P.F. Le Roux[1], Member, IEEE, A.O. Akumu[1]

[1]Tshwane University of Technology, Department of Electrical Engineering, eMalahleni Campus, Witbank, South-Africa.

Corresponding author: P.F. Le Roux

Abstract

Distribution network reconfiguration is categorised as a complex optimisation problem. The main goal for these problems is to determine the optimal path with the least power losses. Once this goal is achieved, a second goal is to achieve the best computation time possible. Reconfiguration of a distribution network is a cost-effective solution to improve the overall efficiency compared to other optimisation techniques. Multiple different algorithms may converge at the same optimal solution; however, not with the same computation time. Therefore, a Genetic Algorithm with an improved selection function, Rank-Weight selection, and multiple constraints are proposed. The proposed optimisation technique is used to search a population of switches for the optimum path in the distribution power network. The population of the GA contains several chromosomes, represented by a string of binary values. Because only radial networks are feasible solutions, the fundamental loop approach is implemented to improve the search and eliminate nearly all non-feasible solutions. The chromosomes will only consist of open switches in the network, reducing the computation time. By combining all these techniques, the computation time to find the optimal solution was improved.

Keywords: Constraints, Fundamental Loop, Genetic Algorithm, Network Reconfiguration, Power Losses, Rank-Weight Selection.

I. INTRODUCTION

With today's economy and at the rate the world is evolving, electrical power is an essential resource. The power grid to transfer power from the generation stations to the consumers was designed many years ago, where calculated estimations were made on the load size. Unfortunately, most of these load limits were already reached. Various engineering solutions may be implemented to assist with the shortage of power; however, it is not always allowed by the economy and finance. Therefore, research should be conducted on cost-effective solutions.

One of these solutions will be to optimise the power losses on overhead lines and cables to improve the overall efficiency. Power systems are designed as ring-feeds where all loads may be supplied using different routes. However, they operate as radial networks by opening their sectionalising-or-tie switches [1], [2]. Because of these ring-feeds, the power network can be reconfigured by opening or closing sectionalising-or-tie switches to achieve the optimum path with the least power losses.

The research was conducted on multiple techniques to establish the optimal configuration of power networks. Merlin and Back [3] proposed a branch and bound type heuristic method. These two engineers made the first publication on network reconfiguration in 1975 and were improved by Shirmomohammadi et al. [4] in 2002 by reducing the computation time. This was achieved by applying a more efficient load flow algorithm. Baran and Wu [5] determined the power losses due to branch exchange using the DistFlow Method Estimation of Power Flow with Backward & Forward Update.

Taleski and Rajicic [6] researched a heuristic technique where different loops were formed in a distribution network, and each loop's power losses were calculated one at a time. This was a good technique; however, extremely time-consuming. Nguyen et al. [7] researched reconfiguration methods and proposed an improved cuckoo search algorithm (ICSA) [8]. They found that this method can obtain the optimal solution with much fewer iterations than the traditional CSA and other improved versions. A stochastic fractal search (SFS) algorithm [9] with distribution generators (DGs) for reconfiguration of a distribution network was proposed by Tran et al. [10], where they used the loss sensitivity factor (LSF) to determine the optimal location for the DGs. SFS was then applied to find the best configuration for the network.

In 2008, Niknam et al. [11] researched a Multi-objective Modified Honey Bee Mating Optimisation (HBMO) method to solve the reconfiguration problem. Their method was successful with an improvement in the computation time. One year later, Niknam [12] improved the computation time of his Multi-objective Modified HBMO algorithm by creating an efficient hybrid evolutionary algorithm based on Particle Swarm Optimisation (PSO) [13] and HBMO techniques.

Carpaneto and Chicco [14] presented a case study where the Ant-colony Search-based technique was used. The results obtained were improved by comparison to the Simulated Annealing (SA) algorithm. Shortly after, in 2010, Linh and Anh [15] studied the application of the Artificial Bee Colony (ABC) algorithm for the reconfiguration of a power network. The optimal solutions were found; however, not with good computation time.

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The Plant Growth Simulation (PGS) method is a non-linear programming tool to solve network reconfiguration problems. This PGS method considers objective functions and constraints separately with no external parameters required [16]. Nara, et al. [17] conducted research on the traditional Genetic Algorithm [18], [19]. The GA may be considered for a discrete or continuous optimisation problem. Patel et al. [20] used the traditional GA to find the optimal solution and then improved it by implementing Distribution Generators (DGs) [21]. An improved GA was proposed by Abubakar et al. [22], where they compared their results to similar methods and obtained very good results. Enacheanu et al. proposed a GA based on the matroid theory [23], where Zhu proposed a refined GA [24]. Jakus et al. proposed a hybrid heuristic GA where their objective functions were to reduce the network power losses and the network loading index to improve the overall efficiency. The algorithm was successful with high quality and accuracy with a remarkable short execution time [25].

In this research paper, a Genetic Algorithm with an improved selection function, Rank-Weight selection, and multiple constraints are proposed. The proposed GA technique is applied to the power network reconfiguration optimisation problem. Furthermore, the Rank-Weight selection algorithm is integrated with multiple constraints to achieve the optimal solution at a novel computational time. The proposed method is executed on three IEEE power test networks: i) Civanlar's IEEE 16-bus network, ii) Baran and Wu's IEEE 33-bus network, and iii) the Taiwan Power Company (TPC) IEEE 83-bus network to analyse the robustness, reliability, and computation time of the technique. The convergence and computation time are then compared to similar techniques to measure the performance.

II. THEORETICAL CONSIDERATIONS

A. OBJECTIVE FUNCTION

This research paper aims to reduce the power losses by determining the optimal radial path with the proposed Genetic Algorithm while satisfying the constraints. The objective function may be expressed mathematically as [17]:

$$\text{Minimize} \qquad P_{loss} = \sum_{b=1}^{N_r} R_b . i_b^2 \qquad (1)$$

Where,

P_{loss} is the active power losses,

N_r is the total number of branches,

R_b is the resistance of the branch, and

i_b is the current flowing through the branch.

The objective function is subjected to the following constraints:

1) Radial network - no loops may be formed.
2) Islanding - no-load may be isolated without supply.
3) Voltage profile - should be in the correct range:

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

4) Power flow - each node should not exceed the maximum capacity limit to keep the network balanced.

$$S_i \leq S_i^{max}$$

These constraints mentioned are extremely important to filter the outcomes and provide a feasible solution. Each constraint will be discussed in-depth in the next section.

B. OBJECTIVE FUNCTION CONSTRAINTS

1) RADIAL NETWORKS

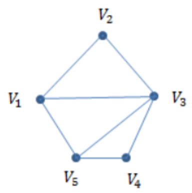
The first constraint is to identify if a solution is radial or not. Should a loop form, the solution will be non-feasible. The constraint should identify and assign a penalty factor to the specific chromosome; thus, providing the chromosome with a smaller probability for mating.

To identify radiality, an identity matrix should be formed. When a solution is populated, a node may not be repeated in the identity matrix. Once this occurs, it can be concluded that a loop is formed.

2) ISLANDING

All loads in the network should be connected to a source to achieve an accurate load flow. For this reason, a function is proposed to determine if any islands formed with each solution. Should a load be disconnected from the network, a penalty factor will be assigned to the chromosome, giving it a small mating probability.

In Figure 1, a five-node network is illustrated with an adjacency matrix A. Because there are five nodes in the network, matrix A is a 5x5 matrix. Based on graph theory, it can be determined that there is a relationship between a network and an adjacency matrix.



$$A = \begin{bmatrix} 0 & 1 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 & 0 \\ 1 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 1 & 0 \end{bmatrix}$$

FIGURE 1: Adjacency matrix.

A network is disconnected if, for some labelling, the adjacency matrix A can be partitioned into sub-matrices A_{11}, A_{12}, A_{21}, $and\ A_{22}$, where A_{11} and A_{22} are square matrices [26].

$$A = \begin{bmatrix} A_{11} & 0 \\ 0 & A_{22} \end{bmatrix}$$

3) VOLTAGE PROFILE

The voltage constraint will guide the solutions to be in the correct range (0.95≤V_i≤1.05). This is important since the voltage profile of a network directly impacts the efficiency of a network. The closer the voltage is to 1 per unit, the higher the efficiency and the higher the chances of finding the optimal solution.

Therefore, should the voltage be out of range, a penalty factor will be assigned to the specific chromosome where its mating probability will reduce.

4) POWER FLOW

For the final constraint, each node's power flow should not exceed the maximum capacity limit to keep the network balanced.

C. FUNDAMENTAL LOOP APPROACH

Should one switch in a loop be opened, virtually all solutions would be feasible. Should one solution not be feasible, a penalty factor will be assigned to the chromosome. Fundamental loops (FLs) may be mathematically expressed as:

$$FL = N_r - N + 1 \quad (2)$$

Where,

FL is the number of fundamental loops,

N_r is the number of branches, and

N is the number of nodes.

Therefore, it may be concluded that the number of fundamental loops is the number of switches opened in the network. By using Civanlar's network, illustrated in Figure 2, as an example, the fundamental loop approach may be explained.

Should all switches in the network be closed, three fundamental loops will form. For the algorithm to find the optimal solution in the shortest time, all constraints should be accounted for. The three loops in Civanlar's IEEE 16-bus network may now be presented as:

$$\text{Loop}_1 = [L_1\ L_2\ L_3\ L_4\ L_5\ L_6]$$

$$\text{Loop}_2 = [L_6\ L_7\ L_8\ L_9\ L_{10}]$$

$$\text{Loop}_3 = [L_2\ L_3\ L_4\ L_5\ L_7\ L_8\ L_9\ L_{11}\ L_{12}\ L_{13}\ L_{14}\ L_{15}]$$

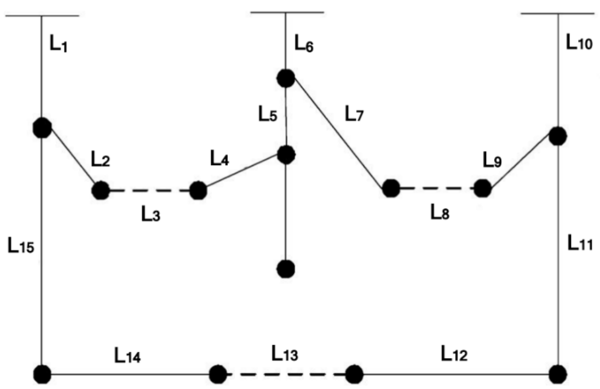


FIGURE 2: Civanlar's network.

In each of these three loops, a switch may only be opened once. Should a switch be opened for the second time in a different loop, a loop will form; thus, the solution will not be radial.

III. PROPOSED GENETIC ALGORITHM METHODOLOGY

The proposed GA may be used as an optimisation technique. For this research paper, it will be used to optimise power losses in a distribution network. All functions of the proposed GA will be explained in this section. In Figure 3, the flow diagram is revealed.

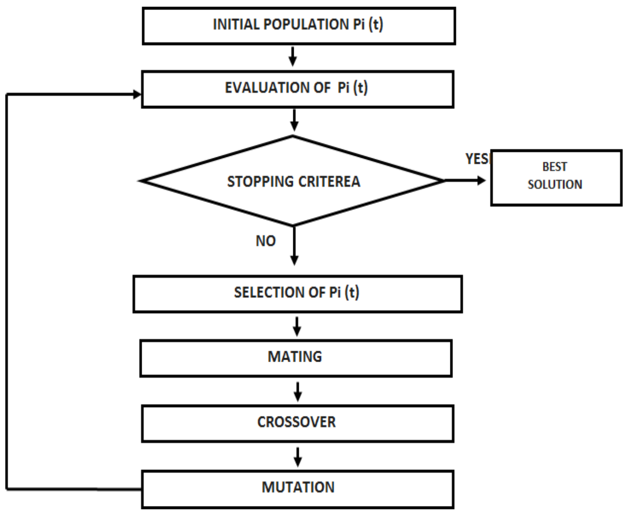
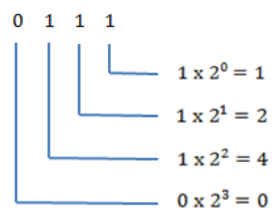


FIGURE 3: Proposed Genetic Algorithm flow diagram.

A. DECODING

The population will consist of several chromosomes that will symbolise the network's opened switches [27]. Below is an example of a chromosome for a radial solution:

Consider a 4-bit chromosome (0 1 1 1). Decoding of this chromosome will follow:



Therefore,

$$S_i = 0111 = 2^3 \text{x}\, 0 + 2^2 \text{ x } 1 + 2^1 \text{ x } 1 + 2^0 \text{ x } 1 = 7$$

Every variable X_i will have an upper and lower limit:

$$X_i^L \leq X_i \leq X_i^U$$

Because the upper (1111) and lower (0000) limits are known, the value for any 4-bit chromosome may be mathematically obtained as [28]:

$$X_i = X_i^L + \frac{(X_i^U - X_i^L)}{(2^{ni} - 1)} \text{ x } (S_i) \quad (3)$$

B. GENETIC FUNCTIONS

Genetic functions utilised in Genetic Algorithms retain genetic diversity. With the research conducted, most research papers use the traditional GA functions for the reconfiguration problem [29].

By keeping the distribution network radial, these functions have less non-feasible solutions to filter; [30] thus, improving the computation time.

Each function of the proposed GA will now be discussed:

1) Selection / Reproduction,
2) Crossover / Recombination, and
3) Mutation.

Before we discuss each function in-depth, the population size of the GA needs to be addressed. The population size contains numerous chromosomes. Should the population be too large, the algorithm will have more chromosomes to work through; thus, the computation time will increase. However, should the population be too small, the optimal solution might not be obtained because of the small search space. The population size is dependent on the encoding as well as the type of objective function. Research has shown that when the population is decreased below a certain threshold, the algorithm does not find the optimal solution faster.

1) Selection / Reproduction

The first function to be discussed is reproduction. Two chromosomes are selected from the population to be the parents, where the crossover will be performed to generate the offspring. With the inspiration of Darwin's evolution theory, "survival of the fittest" [31], the fittest chromosome should survive and produce offspring. Because the objective function is to minimise, the chromosomes will be arranged according to their fitness, from the smallest value to the largest. Thus, the smaller the chromosome value, the fitter the chromosome and the higher the probability of contributing offspring to the next generation. Once this is accomplished, the selection procedure may continue.

Multiple functions were developed to improve the selection of the chromosomes. However, the Rank-Weight selection algorithm was selected due to the rapid computation time. The Rank-Weight selection algorithm is problem independent and determines the probability from the rank *n* of the chromosome [32]:

$$P_n = \frac{N_{Keep} - n + 1}{\sum_{n=1}^{N_{Keep}} n} \tag{4}$$

The cumulative probability indicated in Table 1, column 4, is used to select the chromosomes. The procedure is as follows: a random value between 0 and 1 is generated. Initially, $n = 1$, the first chromosome with a cumulative probability greater than the random number generated, will be selected for the mating pool; i.e., the random number generated is $r = 0.577$, where r is greater than 0.4 (first row); thus, $n = 2$ will be selected.

TABLE 1: Rank-Weight selection algorithm.

n	**Chromosome String**	P_n	$\sum_{i=1}^{n} P_i$
1	00010111001101	0.4	0.4
2	11010011001010	0.3	0.7
3	10100101101100	0.2	0.9
4	00001111010110	0.1	1.0

Rank-Weight selection's advantage is that all the probabilities will only be calculated once for the given objective function; therefore, improving the computation time. With this, the probability rate may be applied more broadly, i.e., retaining the two or three best solutions of the population size. However, the overuse of this rate may lead to premature convergence of the incorrect solution.

2) Crossover / Recombination

After the selection function was completed, the crossover function will commence. The crossover is a function that combines two fit chromosomes to produce new chromosomes that are known as the offspring. Should the best features of both chromosomes be used, the new chromosomes will be of higher quality. For most of the research conducted, the traditional point-to-point crossover was used. This function will now be explained:

An interposition G in a chromosome will be selected randomly between 1 and L-1, where L is the chromosome's length. Once G's position is established for two chromosomes, the bit at G+1 will be exchanged between these two chromosomes. For example, G = 3.

$X_1 = 100|10$

$X_2 = 110|01$

Thus, after the crossover occurred:

$X_1' = 10001$

$X_2' = 11010$

Where X_1' and X_2' are the offspring formed.

3) Mutation

Lastly, the mutation function occurs. The mutation is a function introduced to maintain genetic diversity from one generation to the next. The mutation occurs during evolution according to the mutation probability. This probability should be as low as 0.01.

The chromosome's mutation is relatively simple, where it will randomly choose a bit in the chromosome and invert the bit from zero to one or visa-versa. This may result in new genes added to the gene pool and may provide improved solutions.

For most of the research conducted on the mutation, the traditional flip-bit method was used. This function will now be explained:

A random bit of the chromosome is selected and changed from zero to one or visa-versa. For example:

$$X_1 = 1101$$

If the mutation occurs in the 3rd bit of the chromosome, the new chromosome will be:

$$X_1' = 1111$$

The mutation is an important function of the algorithm. It is an additional resource to explore the fitness area where new paths may be discovered. The function also assists the Genetic Algorithm to not converge on a popular solution multiple times.

IV. APPLICATION & RESULTS

In this section, the proposed Genetic Algorithm is applied to three IEEE test distribution networks, i.e., Civanlar's IEEE 16-bus network, Baran and Wu's IEEE 33-bus network, and the Taiwan Power Company (TPC) IEEE 83-bus network, as seen in Figure 2, 4, and 5. All data can be found in the Dissertation [33]. The proposed GA was developed using MATLAB R2010a software, with an Intel 2.2 GHz processor, 2GB RAM, personal computer to execute the simulations.

Comparing the traditional GA, the proposed GA with improved selection and constraints, and other methods' results were compiled where the results indicated that all methods converged at the optimal solution. However, the computation time was improved by the proposed GA.

Civanlar's IEEE 16-bus network is seen in Figure 2; multiple researchers found the same optimal solution [34], [35], and [16]. Because of this, it was concluded that the optimal power loss for the 16-bus network is 466.1kW. The original configuration with a power loss of 511.4kW was improved to 466.1kW by obtaining the network's optimal path, as seen in Table 2.

TABLE 2: Civanlar's IEEE 16-bus network results.

Algorithm	Switches Opened	Power Loss (kW)	CPU Time (s)
Original	$L_3\ L_8\ L_{13}$	511.4	-
Traditional GA	$L_4\ L_7\ L_{13}$	466.1	0.92
Proposed Configuration	$L_4\ L_7\ L_{13}$	466.1	0.53
PGSA	$L_4\ L_7\ L_{13}$	466.1	0.62
ABC	$L_4\ L_7\ L_{13}$	466.1	4.9

Baran and Wu's IEEE 33-bus network is the second IEEE test network considered for reconfiguration, depicted in Figure 4. In Table 3, all algorithms noted the same optimal power loss of 139.55kW [24], [36], and [37] with different computation times.

The proposed method's computation time was improved with respect to the other GA algorithms listed in Table 3; however, not for the HBMO.

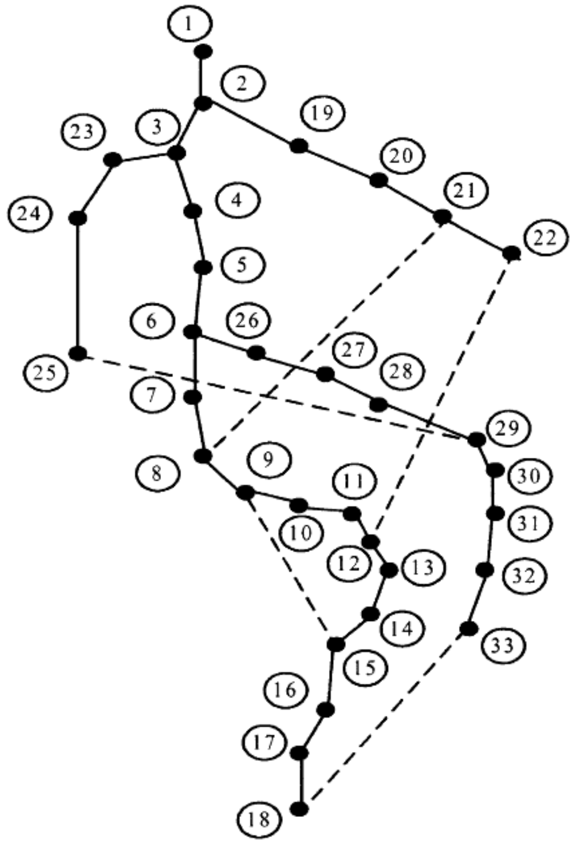


FIGURE 4: Baran and Wu's network.

TABLE 3: Baran and Wu's IEEE 33-bus network results.

Algorithm	Switches Opened	Power Loss (kW)	CPU Time (sec)
Original	$L_{33}\ L_{34}\ L_{35}\ L_{36}\ L_{37}$	202.7	-
Traditional GA	$L_7\ L_9\ L_{14}\ L_{32}\ L_{37}$	139.55	22.6
Proposed Configuration	$L_7\ L_9\ L_{14}\ L_{32}\ L_{37}$	139.55	13.42
HBMO	$L_7\ L_9\ L_{14}\ L_{32}\ L_{37}$	139.55	14
GA	$L_7\ L_9\ L_{14}\ L_{32}\ L_{37}$	139.55	30

The third and final IEEE test network considered for reconfiguration is the Taiwan Power Company (TPC) IEEE 83-bus network, seen in Figure 5. Table 4 illustrates all the algorithms that concluded the same optimal power loss of 469.88kW with different computation times [38], [35], and [39]. An improvement can be seen in the computation time with the proposed GA compared to the other methods listed.

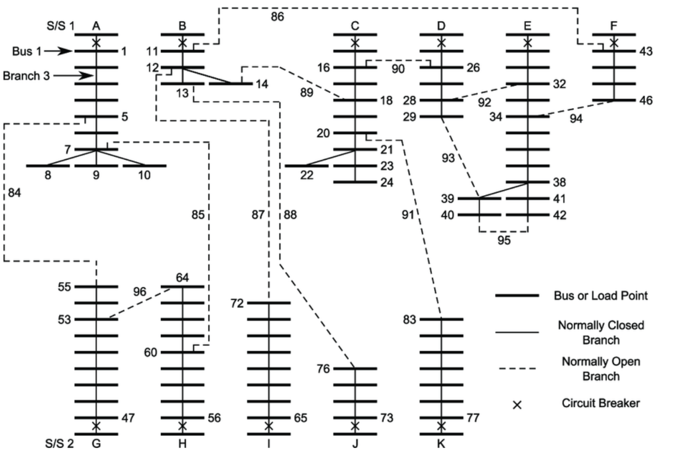


FIGURE 5: The Taiwan Power Company network.

TABLE 4: The Taiwan Power Company (TPC) IEEE 83-bus network results.

Algorithm	Switches Opened	Power Loss (kW)	CPU Time (s)
Original Configuration	L_{84} L_{85} L_{86} L_{87} L_{88} L_{89} L_{90} L_{91} L_{92} L_{93} L_{94} L_{95} L_{96}	532.0	-
Traditional GA	L_{55} L_{62} L_{7} L_{72} L_{13} L_{89} L_{83} L_{90} L_{92} L_{39} L_{41} L_{34} L_{86}	469.88	146.2
Proposed Configuration	L_{55} L_{62} L_{7} L_{72} L_{13} L_{89} L_{83} L_{90} L_{92} L_{39} L_{41} L_{34} L_{86}	469.88	120.4
APSO	L_{55} L_{62} L_{7} L_{72} L_{13} L_{89} L_{83} L_{90} L_{92} L_{39} L_{41} L_{34} L_{86}	469.88	152.91
PSOA	L_{55} L_{62} L_{7} L_{72} L_{13} L_{89} L_{83} L_{90} L_{92} L_{39} L_{41} L_{34} L_{86}	469.88	152.91

V. CONCLUSION

The objective of this research paper is to determine if the proposed Genetic Algorithm technique is feasible and reliable for reconfiguration of a power distribution network to achieve the optimal solution according to the objective function. When the objective was reached, a second objective was considered, improvement of the computation time.

The research was conducted on several algorithms to identify their optimal solutions and the time the algorithms took to converge. By studying the results obtained in Tables 2, 3, and 4, it was concluded that the computation time of the proposed Genetic Algorithm was improved by integrating an improved selection function called Rank-Weight selection to improve the number of iterations required to achieve the optimal solution.

Herewith, multiple constraints were added to improve the filtering process of non-feasible solutions. With these two improvements, the computation time for the proposed algorithm was reduced. Thus, the proposed Genetic Algorithm may be classified as an effective and reliable algorithm during the planning and operation phase of a distribution network to enhance the efficiency and performance.

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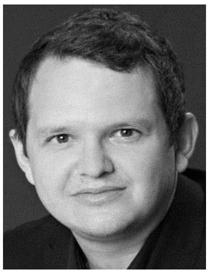

PF Le Roux was born in South Africa in 1988. He received his Bachelor's degree in Electrical Engineering in 2010. He pursued his Master's degree in Electrical Engineering in 2012 from the Tshwane University of Technology. Simultaneously, he pursued his Master of Science in Electronic and Electrical Engineering from the French South African Institute of Technology. Both qualifications were completed in 2013. After a few years in the field as a project engineer, design engineer, and engineering consultant; he received his Professional Engineering status from the Engineering Council of South Africa (ECSA) in 2016. He is also registered with the South African Institute of Electrical Engineers (SAIEE) since 2016 and the Institute of Electrical and Electronics Engineers (IEEE). Furthermore, he pursued his Ph.D. Degree in Electrical Engineering and graduated in 2018 from the University of Pretoria with honorary colours. He is currently a Senior Lecturer at the Tshwane University of Technology, South Africa, in the field of Power, Protection, Renewable Systems, and Control.

AO Akumu graduated with an MSc degree in Electrical Engineering in 1994 from Poznan Technical University, Poland, and a DEng degree in Electrical Engineering in 2003 from Ehime University, Japan. He is currently a Senior Lecturer at the Tshwane University of Technology, South Africa. His interest is in the condition monitoring of power transformers, artificial intelligence, and smart grids.