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Sensor placement algorithm for faults detection in electrical secondary distribution network using dynamic programming method: focusing on dynamic change and expansion of the network configurations

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Abstract

Modern power grids are developing toward smartness through the use of sensors in gathering data for situation awareness, visibility, and fault detection. In most developing countries, fault detection in the electrical secondary distribution network (SDN) is very challenging due to the lack of automated systems for network monitoring. Systems for monitoring faults require sensor placement on each node, which is not economically feasible. Hence, optimal placement algorithms are required to ensure that the network is observable with few sensors possible. The existing sensor placement methods based on mathematical and heuristic approaches are efficient for transmission and primary distribution networks which are mostly static in size and layout. Such methods may not be efficient in SDN which is dynamic in size and have a relatively large number of nodes. This study proposes an enhanced dynamic programming method for sensor placement to enhance fault detection in SDN. The proposed algorithm employs the depth search concepts and the parent–children relationship between nodes to determine sensor types and locations considering the optimal cost. The proposed algorithm was compared with other methods including particle swarm optimization, genetic algorithm, and chaotic crow search algorithm using different network configurations. The results revealed that the proposed algorithm suggested the minimum number of sensors and shortest convergence time of 1.27 min. The results also revealed that, on network expansion, maintaining the location of the existing sensors is more cost-effective by 20% than reallocating the existing sensors. Furthermore, the results revealed that an average of 30% of nodes, need sensors to observe the entire network, hence cost optimization.

Keywords: Fault detection, Placement algorithm, Dynamic programming, Internet of things, Secondary distribution network, Remote sensing unit

Introduction

Key economic and social activities, including industries, schools, hospitals, households, and government and non-government offices, highly depend on the efficient and reliable power supply. In many developing countries, electrical faults are currently detected and reported by consumers or utility personnel through visual inspection. The entire process is inefficient as it takes excessive time to detect and report faults through phones, ineffective troubleshooting techniques, and inadequate tools to identify and classify faults [1]. Utilities worldwide are working to ensure energy efficiency and reliability by employing various modern approaches, technologies, and mechanisms, leveraging the advancements in information and communications technology [2]. These technologies aim to ensure that the network is monitored for immediate fault detection to enhance the reliability of the electrical network.

In transmission networks, fault detection is achieved through network monitoring systems such as the Supervisory Control and Data Acquisition (SCADA) [3, 4]. In primary distribution networks, fault detection and network monitoring are done through the Distribution Management System (DMS) [5]. The advancement in metering technologies has realized the use of automatic meter readings (AMR) for monitoring distribution networks up to the distribution transformers [6]. The development of sensor technologies revealed the use of IoT-based sensors for electrical network monitoring applications [7–9]. However, most of the existing studies for fault detection in electrical distribution networks were designed based on transmission and primary distribution networks which are considered stagnant over time. These techniques may not be very efficient in secondary distribution networks. The electrical secondary distribution networks are very complex due to their radial topology, excessive number of nodes, dynamic expansion, accessibility, and coverage [10, 11]. The electrical SDN connects the end-users to the network; hence, they are frequently changing due to new customer connections which results in frequent network reconfigurations [12].

In current electrical grids, faults are detected through the processing of data collected from installed sensors. Sensors form a significant part of electrical network monitoring and control. For efficient data collection across the network for control, there should be sensors throughout the distribution network. For obvious economic reasons, it is not feasible to fully deploy meters and sensors throughout the entire electrical network especially the SDN with a larger number of nodes. Therefore, optimal sensor placement is one of the key factors in determining the efficiency of the fault detection system. The placement method should determine where to place sensors to ensure maximum observability with minimum sensors. It is necessary to optimize the number and location of sensors while minimizing operation costs and improving reliability. There are several sensor placement methods in electrical networks such as heuristic, metaheuristic, and deterministic [13].

Heuristic methods are often used to accelerate the process of finding a reasonable solution when an exhaustive search is impractical. The final optimal outcome from the heuristic method cannot be guaranteed. Examples of heuristic methods include depth-first, domination set, and greedy algorithms [13]. The metaheuristic method is an improvement of the heuristic method, which involves intelligent search processes that can deal with discrete variables and non-continuous cost functions. This method combines a randomized algorithm and a local optimization algorithm to solve the optimization problem. Notable examples of metaheuristics methods include genetic/evolutionary algorithms, tabu search, simulated annealing, colony optimization, and particle swarm optimization [14]. The heuristic and metaheuristic methods are time-consuming due to the involvement of iterative processes and mostly they include convergence assumptions that cannot be satisfied in the real world. Deterministic algorithms can predict the behavior of the system when given a particular parameter as an input. Unlike heuristic and metaheuristic, the deterministic algorithms are accurate and time-effective. Examples of deterministic algorithms include integer programming, binary search, and dynamic programming [15].

Deterministic methods based on state estimation techniques were proposed by several previous studies. Sensor placement methods using phasor measurement units (PMU) have been reported for data collection in transmission and primary distribution networks [16]. Other techniques based on grid state estimation were also reported [17]. Another technique for optimal meter deployment and minimizing errors in voltage estimations in primary distribution networks was proposed by Nusrat [18]. Banda Srinivas [19] proposed a technique based on binary integer programming algorithms to improve the processing capability of state estimators in detecting bad data. The method focused only on sensors placed on substations considering the Institute of Electrical and Electronics Engineers (IEEE) 14-bus system which is very small as compared to the real SDN. A study done by Singh et al. [20] proposed a PMU Placement mechanism for maximum observability of power systems under voltage stability and intensely islanding contingencies using integer linear programming (ILP). Another study was done by Samudrala et al. [21] on sensor placement for outage identifiability in low-voltage power distribution networks using a dynamic programming method. The study by Samudrala et al. [21] revealed the promising performance of the dynamic programming (DP) method in a radial network.

The existing algorithms for sensor placement mainly focused on transmission and primary distribution networks. Considering the characteristics of SDN and its dynamic nature, such approaches may not be efficient. Also, in such a dynamic network there are many possible scenarios to consider such as the possibility of shifting sensors, adding new sensors, or maintaining sensor positions when the network changes. Therefore, this study proposes an algorithm for sensor placement in the electrical SDN considering the changing network topology. The proposed algorithm can accommodate the large size of the network and considers the cost of sensor placement in ensuring network observability. This paper is organized into four sections: section "Related works" presents the related works highlighting the weaknesses of the previous studies and focus of this study. Section"Methods" presents the methods for this study with explanations on the network modeling, rules, and proposed algorithms. Section "Results and discussion" presents the results and discussion starting from methods comparison where PSO, GA, CCSA, and DP were compared. The results of the proposed algorithm when executed on different scenarios, including network expansion and changing of the root node, were analyzed and results were extensively discussed. Section "Conclusion" provides the conclusions and highlighted recommendations for future work.

Table 1 Summary of the related works

SN	Study	Main considerations	Concept proof	Weakness
1	Samudrala et al. [21]	Outage identifiability. Zero Insertion Bus and Network expansion	IEEE 37 and IEEE 123 feeders	Did not analyze the costs on either fixing or shifting the sensors when the network expands. Did not consider the DG
2	Patil et al. [37]	Single PMU loss and Zero-Injection Bus conditions	Computer simulation results with IEEE 14, IEEE 39, IEEE 118, and KPTCL 155	Limited to transmission and primary distribution network and did not consider network topology and expansion
3	El-Sehiemy et al. [38]	Observability depth, measurement redundancy, and robustness of the method under Contingencies	Applied to five benchmark systems IEEE 14-bus, 30-bus, 39-bus, 57-bus, and 118-bus	Limited to transmission and primary distribution network and did not consider network topology and expansion
4	Kaur and Kaur [39]	Measurement redundancy	The algorithm has been tested on IEEE 14-bus, 18-bus, 24-bus, 30-bus, 34-bus, IEEE 69-bus and 118-bus	Did not take considerations on the large systems with more than 1000 buses and topological behavior
5	Singh et al. [20]	Voltage stability-based contingency and intensely islanding	Simulations done using IEEE 14,30,118-bus New England 39-bus and Indian NRPG 246-bus	Limited to small network and did not address network topology and expansion
6	Armendariz et al. [22]	Considered the presence of smart meters and pseudo-meters for observability	Cigré LV benchmark grid	Did not consider unbalance behavior, sensitivity bus and future network expansions
7	Gopakumar et al. [40]	Measurement redundancy, conventional measurements and Single PMU outage	IEEE standard bus systems, western region Indian power grid (WRIPG) and the southern region Indian 7power grid (SRIPG)	Small-sized network with simulation results up to a maximum of 321. The study did not also consider the network growth factor
8	Puri and Brar [41]	Cost and observability	Simulation using IEEE 9, IEEE 39, IEEE 68-bus systems	Focused on transmission network and did not consider reliability and topological changes
9	Mazhari et al. [26]	Line outages and PMU losses	IEEE standard test systems as well as the Iranian 230- and 400-kV transmission grids	Based on the transmission and did not address key issues including bus sensitivity, DER, and expansion
10	Gao et al. [42]	Cost and observability	Numerical simulation results of IEEE 14-bus and New England 39-bus system	No considerations on reliability, network expansion, and redundancy
11	Baldwin et al. [43]	Observability and cost	Computer simulations	Limited by computational time and burden

Related works

Several literature works were reviewed and recognized significant work conducted on the optimal sensor placement realm. However, it was also noted that very few of them focused on the electrical SDN [22]. This is mainly because the network size is comparatively larger with an excessive number of nodes. In addition to that, most of the related works in the literature proposed algorithms focused on constraints, including Zero Insertion Bus (ZIB), single PMU loss, one-line outage, bus sensitivity, islanding mode, conventional measurement, and topological considerations. However, limited studies, including Ashish [23], considered the practical/field parameters, including dynamic network expansion, which is crucial in low-voltage networks as the network keeps on growing every day due to new customer connections. The customer data gathered from the national utility company in Tanzania from January 2015 to September 2019 have revealed a growth rate of 32% per year. This growth rate is significant for the distribution network and impacts the sensor placements for fault detections, hence needs to be addressed. Another constraint that most previous studies have rarely considered is the inclusion of DER in the network to operate in islanding mode, which is a vital characteristic of the modern electrical SDN and can be achieved when the algorithm accommodates the root node reconfigurations. The study done by Alnajjab et al. [24] proposed the sensor placement algorithm using dynamic programming for the distribution network, which worked well. However, it only focused on outage detection and not fault detection. Furthermore, it did not consider the inclusion of the DER in a network and analysis of the placement when the network expands

Again, most of the literature used numerical/mathematical approaches, including integer programming methods for sensor placement algorithms. A numerical solution requires overwhelming computational effort, which increases exponentially as the problem's size increases (the curse of dimensionality) [25] thus not recommended for extensive network, especially for the electrical SDN. Heuristics algorithms, including genetic algorithms and particle swarm optimizations, have also been used by most studies for the transmission network and primary distribution network but do not work well with SDN due to its radial nature and complexity. This study proposes the dynamic programming method which is more appropriate in electrical SDN. The study also incorporated the key constraint for electrical SDN including dynamic expansion and root node changing. Table 1 presents the summary of the related works with their key considerations and weaknesses.

Methods

Distribution network modeling

An electrical distribution network can be modeled as a radial graph $G = \{V, E\}$ with N nodes, where V is a set of vertices on the network or nodes/buses, and E is a set of branches or edges [21]. In a radial distribution network, power flows from upstream to downstream buses. In that regard, power can flow from node i (upper) to node j (down) via a branch which can be represented as branch/edge (i,j). For example, from Fig. 1, power can flow from node 1 to node 2 via branch which can be presented as branch (1,2). The immediate upstream node i is a parent of node i and the immediate downstream node of node i is a children of node i. Therefore, P_i is a set of all parents of node i and C_i is a set of all children of node i. However, each node, except the root node, has just one parent for the radial distribution network. For example, from Fig. 1, the parent of node 4 is node 2, and the children of node 4 are nodes 7, 8, and 9. The set of edge that connects a node to its parent is called a parent edge, and the set of edges that connects a node to its children is called children edge. Consider node 4 in Fig. 1, the parent edge is an edge (2,4), and children's edges are edge (4,7),(4,8), and (4,9). For every node i, the degree of node d_i is a total number of branches that directly connect to node i. The distance between any two nodes can be measured by the number of edges between the two nodes. For example, the distance between nodes 1 and 12 is 4 since there are four edges between them. The node whose number of degrees is greater than 2 is called junction node. For example, the nodes 2 and 4 are junction nodes. Therefore, at this point, we can now define essential variables in our proposed algorithm called a node depth (D_n) and network depth (T). Therefore, at this point, we can now define essential variables in our proposed algorithm called a node depth (D_n) and network depth (T). A depth of a node is the distance between a node and the root node. The depth of a network is the distance between the root node and the furthest node from the root node, i.e., $T = \text{Max}_{n \in V}(D_n)$.

In distribution networks, nodes can also be classified based on their position in the networks such as terminal nodes, intermediate nodes, and common nodes. The common node presents the junction node connecting more than three network segments; for example, node 2 and node 4 in Fig. 1. The terminal nodes present the endpoint of the distribution network segment, which are nodes 7, 9, 11, 12, and 1. The intermediate nodes are nodes between common nodes and end nodes, for example, node 8. The end node that connects the network to the power system is called the root/reference node. Loads and distributed generators can be connected to the nodes. Nodes with no power consumption demand no power injections are called zero-injection nodes.

Observability rules for sensor placement

In placing sensors, it is not feasible to install sensors on each node, especially for the electrical SDN where the number of nodes is significantly high. The observability rules are used to determine the optimal locations for placing sensors in electrical networks [26]. The main goals of the rules are to determine the voltage and current values in some of the nodes without physically installing the sensors in those nodes. There are many established rules for sensor placements, some of the rules used in this study are reported and numbered as follows:

1. **Direct measurements (Rule Number 1):** Rule number 1 states that, when a sensor is installed at a node, the voltage values of a sensor-equipped node and current values of all joint lines are available [27]. Consider Fig. 2, when a sensor is placed at node 1, the voltage values of node 1 and current values of joint branches (1,2) and (1,3) are available. These measurements are obtained directly from sensor.
2. **Bus Voltage Using Pseudo-Measurement (Rule Number 2):** This rule states that, when the voltage and current values of one end of a line are known, the voltage values at the other end of the line can be obtained. Consider Fig. 2 and line between nodes 1 and 2, when voltage values of node 1 and the current values branch (1,2) are

known, then the voltage values of node 2 can be obtained, given that other parameters such as impedance of the branch are known.

3. **Line Current Using Pseudo-Measurements (Rule Number 3):** This rule state that, when the voltage values of both ends of a line are known, the current values of the line can be calculated. Consider Fig. 2, the line between nodes 1 and 2, when voltage values of node 1 and node 2 are known, the current values branch (1,2) can be calculated, given that other parameters such as impedance of the branch are known.
4. **Z.I. Buses Using KCL Equations (Rule Number 4):** The rule states that, if the current values of all branches of zero-injection node are known, except current values of one branch, the unknown branch current phasor can be calculated using Kirchhoff's current law (KCL). Consider Fig. 2, node 2 is a zero-injection node, if current values of branch (1,2) and (2,3) are known, then the current values of branch (2,4) can be calculated using KCL.
5. **Z.I. Bus with Unknown Voltage Phasor (Rule Number 5):** The rule state that, if voltage values of all nodes adjacent to zero-injection node are known, the unknown voltage phasor of zero-injection node can be calculated using Kirchhoff's equations. Consider, Fig. 2, node 2 is a zero-injection node, if the voltage values of node 1,3, and 4 are known, then the phasor voltage of node 2 can be calculated using sing Kirchhoff's equations.
6. **Observability Rule for Radial Network (Rule Number 6-Added rule):** Considering the network given in Fig. 3, the junction node refers to the node with at least one branch for example nodes 1 and 4. An upstream node is the node which the current flows from, for example, node one is an upstream node of nodes 2 and 3, and node 2 is an upstream node of node 4. The rules 1 to 5 presented above mainly focused on the mesh network where each node/bus is a junction node as opposed to the radial network where some of the nodes are intermediate nodes. From Fig. 3, node 4 is observable if a sensor is placed at either upstream node 2 or 2, and node 8 is observable if a sensor is placed either on upstream node 7, 6, or 4. However, placing a sensor in an intermediate node is not cost-effective as placing it in a junction node as it can observe other branches as well. Hence, rule number Six, the added rule in this study, states that a node is observable when a sensor is placed at its next upstream junction node. The voltage and current values are obtained using KCL and KVL. Node 8, node 7, or node 6 are observable if a sensor is placed at their next upstream node number 4. Likewise, node 4 and 2 are observable when a sensor is placed at their next upstream node number 1.

Sensor placement objective function

The primary objective of optimal sensor placement problem based on the topological observability method is to find a minimal set of sensors such that a bus can be reached at least once by the sensor to enhance the observability [28]. The optimal placement of a sensor for an electrical network with N buses can be presented by (1) [29].

$$Y = \sum_{k=1}^{N} w_k x_k \tag{1}$$

Subject to, $A.X \geq b$

$$X = [x_1 x_2 \ldots x_n]^T \tag{2}$$

where $x_i \in \{0, 1\}$.

Y is the optimal set of sensors, w_k is weight factor accounting to the installed sensor's cost at bus k, X is a binary variable vector whose entries are defined as per (2). X is a vector function whose entries are nonzero if the corresponding bus voltage is observable using the given measurement set; otherwise, its entries are zero as presented in (3). The entries of A are defined in (4) and b is a vector whose entries are all ones as shown in (5). Using the objective function in (1) and observability rules, full observability of the network is ensured while minimizing the total installation cost of the sensors.

$$X_k = \begin{cases} 1, & \text{If a PMU is needed at bus } k \\ 0, & \text{Otherwise} \end{cases} \tag{3}$$

$$A_{ij} = \begin{cases} 1, & \text{If } i = j \\ 1, & \text{if } i \text{ and } j \text{ are connected} \\ 0, & \text{Otherwise} \end{cases} \tag{4}$$

$$b = [111 \ldots 1]^T \tag{5}$$

Network information re-organization for changing network topology

Proposed sensor placement algorithm in radial distribution networks

The objective functions for sensor placement and its constraints as presented in (1) to (5) works well in mesh network where each node is a junction node. However, it cannot work well with radial network to incorporate the intermediate nodes. Therefore, for applications in radial distribution networks, the new constraints were proposed in this study as presented in (6).

$$a_{i,j} = \begin{cases} 1, & \text{If } i = j \\ 1, & \text{if } j \text{ is the first upstream junction node of node } i \\ 0, & \text{Otherwise} \end{cases} \tag{6}$$

The proposed algorithms work well with electrical SDN due to the dynamic programming characteristics of dividing the large problems into subproblems to achieve the optimal solution; hence, convergence time could be significantly improved. The proposed method works well on electrical SDN as it is radial and distributed in a tree layout. The algorithm was extended to incorporate the dynamic change of the secondary distribution network and the inclusion of the distributed energy resources (DER) in the network by allowing the root node reconfiguration. The proposed dynamic programming method used the bottom, top tabulation method where the network was modeled starting from the bottom critical nodes. The pseudocode of the proposed dynamic programming method used in this study is presented in Algorithm 1, and the flowcharts are also presented in Figs. 4, 5, and 6. The algorithm design considered minimization of cost, network's dynamic expansion, and Zero Insertion Bus (ZIB) scenarios to determine different network behavior.

Algorithm 1 Pseudocode of the enhanced dynamic programming algorithm

```
Input: Electrical network data
Output: Sensor Locations
Initialization
Load the Objective Functions
Analyze the constraints
Load Electrical network data
Calculate the Maximum network depth (maxdepth)
Get all critical nodes

while i < maxdepth do
    Get critical node at depth i
    for each critical node at depth i do
        List all Children with No Sensors
        Remove all nodes with maximum costs
        Determine the cost-effective Placement
        Update placement vector
    end for
    Checking termination criterion
end while
```

Flowchart for the new network

This scenario is presented when the network is considered to be the new one and the sensor locations have to be determined. The execution started from the critical nodes at the highest depth toward the root node where the depth was zero. The flowchart is presented in Fig. 4.

Flowchart for the expanded network

The algorithm was then enhanced to incorporate the network expansion. In this case, the existing sensor locations of the original network are retained and the placement algorithm suggested the sensor locations on the expanded network. The execution started at the highest depth of the expanded network toward the root node. The solution matrix of the original network is retained and the values are appended with the ones obtained

Table 2 Parameter settings for GA, PSO, CSA, and DP

GA	PSO	CSA	DP
$n = 30$	$n = 30$	$n = 30$	$NodeSensorCost = 2$
$m = 0.01$	$w = 0.4$–0.9	$fl = 2$	$BranchSensorCost = 10$
$c = 0.8, g = 0.9$	$\frac{x_{min}}{10} - \frac{x_{max}}{10}$	AP = 0.1	

n = population/colony/ecosystem size; w = inertia weight; v = limit of velocity; a = distance control parameter from the expanded network to have the final location for the entire network. Figure 5 shows the algorithm flowchart for the expanded network.

Flowchart for the root node reconfiguration

This scenario considered the situation where the root node changes. The algorithm was again enhanced to incorporate this scenario, hence made the network observable regardless of the root node location. The consideration of this scenario provided a way for the DER incorporation in the network without affecting the network observability. The algorithm started by capturing all the possible root node locations, then determined the solution for each of them and finally joining them to have the common sensor locations for the network observability. Figure 6 presents the algorithm flowchart for the root node reconfigurations.

Results and discussion

Description of sensors

The line sensors are connected to the lines to measure the current and voltage flowing through one line. The node sensors are capable of measuring the voltages and current flowing on each line at the nodes. In this study, one of the objectives is to determine optimal sensor placement considering costs. According to Samudrala et al. [21], the node sensors currently available in the market cost two to four times the cost of a line sensor depending on the model and manufacturer. Therefore, in this study, it was assumed that the node sensor costs twice as much as a line sensor. Each sensor node had a gateway to allow interfacing with other smart grid applications to send the readings and accept configurations remotely.

Description of electrical networks for testing algorithms

Different radial networks were considered for comparison in this study, including IEEE 15, IEEE 33, and IEEE 69 systems. Other networks used in this study include 23 nodes network and 47 nodes network which were modified from the standard IEEE bus system. Furthermore, a 79-node network from the Tanzania National Electrical Utility Company was used as a case study. The area is located at Msasani Peninsula along with Kinondoni District in Dar es Salaam, Tanzania. More information on the study area including line data, load data, and network layout can be found in a study done by Kawambwa et al.

Table 3 Nodes observability for 11 node network

Node number	Observability rule	Descriptions	Parameter
1, 2, 3, 4, 5	Rule 1	Direct measurement by node sensors voltage and current	
7, 9, 11	Rule 1	Direct measurement by node sensors	Current
6, 7, 9, 10, 11	Rule 2	Pseudo-measurement	Voltage
	Rule 2	Pseudo-measurement	Current
6, 8, 10	Rule 4	KCL	Current

Table 4 Nodes observability for 23 node network

Node number	Observability rule	Descriptions	Parameter
1, 2, 3, 4, 5	Rule 1	Direct measurement by node sensors	Voltage and current
7, 9, 11	Rule 1	Direct measurement by node sensors	Current
6, 7, 9, 10, 11	Rule 2	Pseudo-measurement	Voltage
	Rule 2	Pseudo-measurement	Current
6, 8, 10	Rule 4	KCL	Current

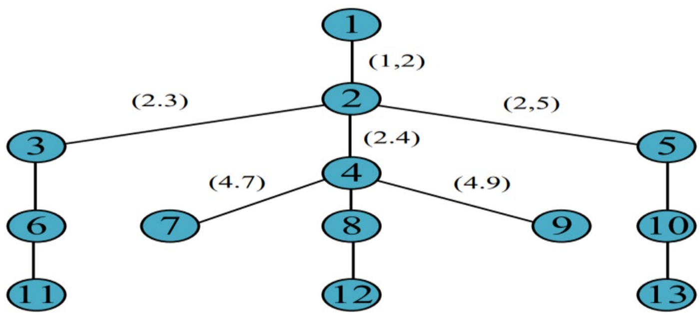

Fig. 1 Representation of distribution network as a tree

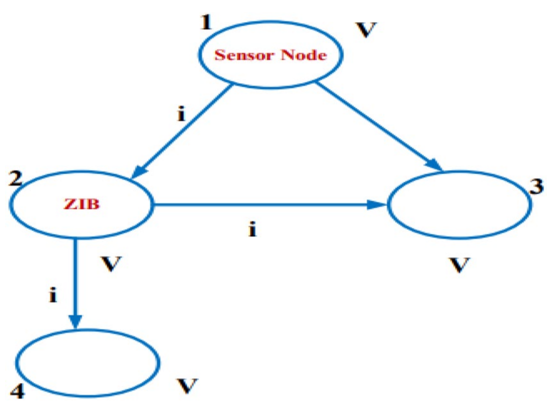

Fig. 2 Sensor placement rules

[30]. From this network, different modified configurations were derived to test the algorithms on different scenarios.

Parameter settings

The proposed algorithm in this study was tested against other algorithms commonly used in optimization for sensor placements in electrical networks such as particle swarm optimization (PSO) [31, 32], genetic algorithm (GA) [33–35], and chaotic crow search algorithm (CCSA) [36]. The comparison for the method was done considering the convergence time, the number of proposed sensors, and their proposed locations. The algorithms were implemented to run 10 times and each run had 1000 iterations. The average

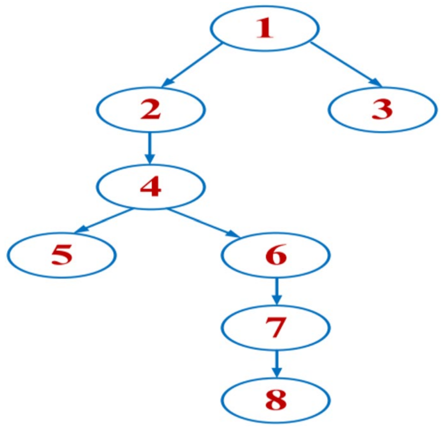

Fig. 3 Observability rule number for radial network

convergence times were captured for each algorithm. Table 2 presents the parameters considered when implementing the algorithms for comparison. The computer that was used in this comparison had an Intel® Processor core i7-8550U @ 1.80GHz (8 CPUs), and 12 GB RAM using Windows 10 64-bit. All algorithms were implemented using MATLAB R2021b.

Performance evaluation of algorithms for sensor placements

Different radial networks were considered for comparison in this study, including IEEE 15, IEEE 33, IEEE 69, 23 nodes network, 47 nodes network, case study network, and the expanded case study network. Figure 7 presents the bar chart comparison on number of proposed sensors in different network and Fig. 8 presents the comparison on the convergence times. The results showed that the dynamic programming method had better performance on both the number of proposed sensor nodes and convergence time. The observed convergence time in minutes was 1.27 for dynamic programming, while others were 2.30, 2.31, and 3.00 for PSO, GA, and CSA, respectively. Due to its cost effectiveness, fast convergence time, and its ability to place sensors in the distribution networks, the DP method was tested for various considering dynamic network scenarios.

Placement results for dynamic electrical network

The performance of the proposed algorithm in handling the dynamic nature of electrical SDN was tested by considering two network scenarios. In the first scenario, a small electrical network with 11 nodes was considered, and then, the same network was expanded to 23 nodes in order to simulate the changing nature of the SDN.

Figure 9 presents the sensor placement algorithm results for the distribution network with 11 nodes. The results show that one node sensor at node 2 and three line sensors at branch (3,7), (4,9), and (5,11) were used to observe the entire network. The functioning of the algorithm considers the rules presented in "Sensor placement objective function" section; therefore, the rest of the branches and nodes without

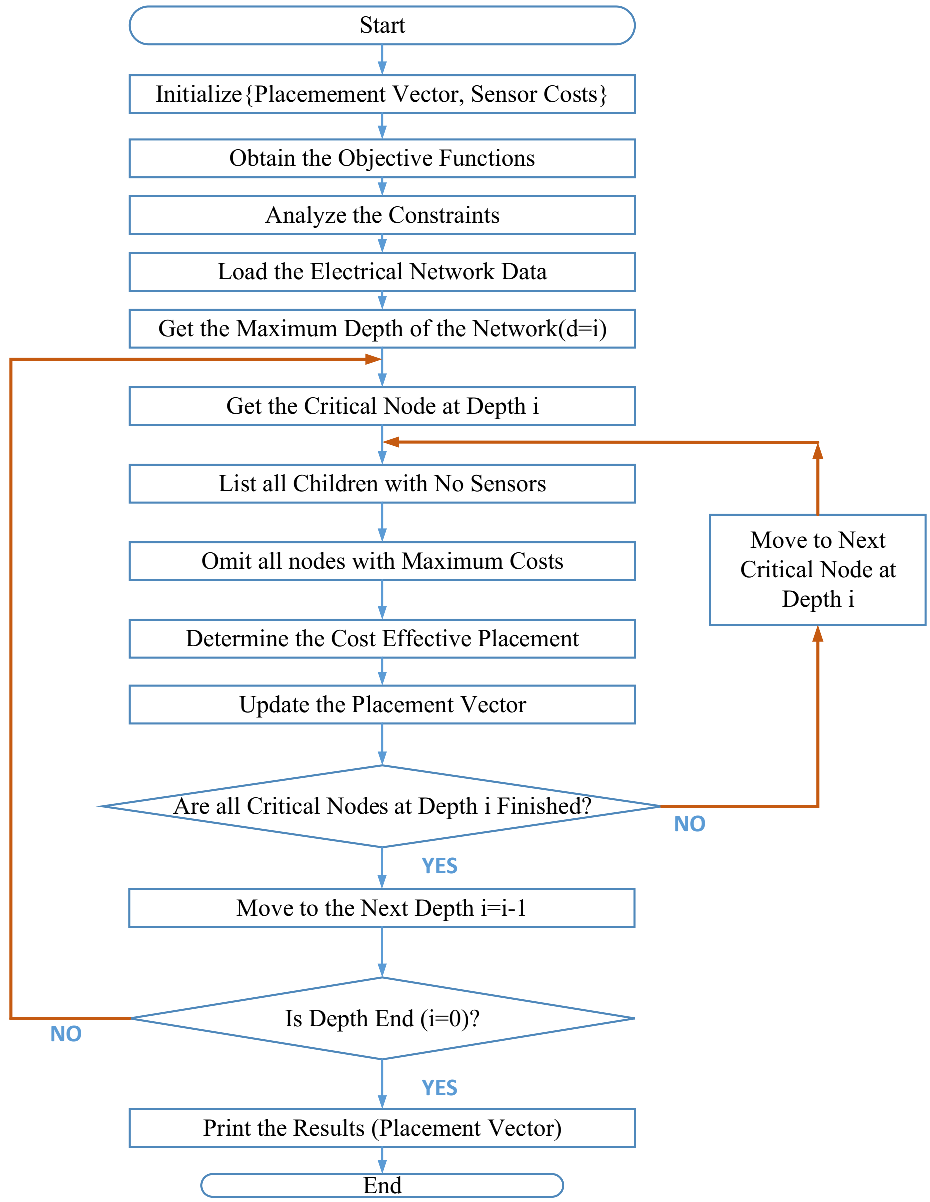

Fig. 4 Algorithm flowchart for new network

sensors can be accommodated using the rules. For example, Table 3 shows how the rules were used to find the observability of the nodes.

Figure 10 highlights a network expansion to 23 nodes where two branches were attached to each node 6, 7, 8, 9, 10, and 11. The results show that that despite the expansion of the network, node sensor was not added and the position of the sensor at node 2 was retained. On such network expansion, the 3, 4, and 5 become branch nodes but no node sensor was placed. This shows that the expansion of the network affects only those nodes whose branches have been increased. The upper branches without any additional branching will not be affected by the network expansion unless a node sensor is introduced in subsequent branches. The observability table of this network is presented in Table 4.

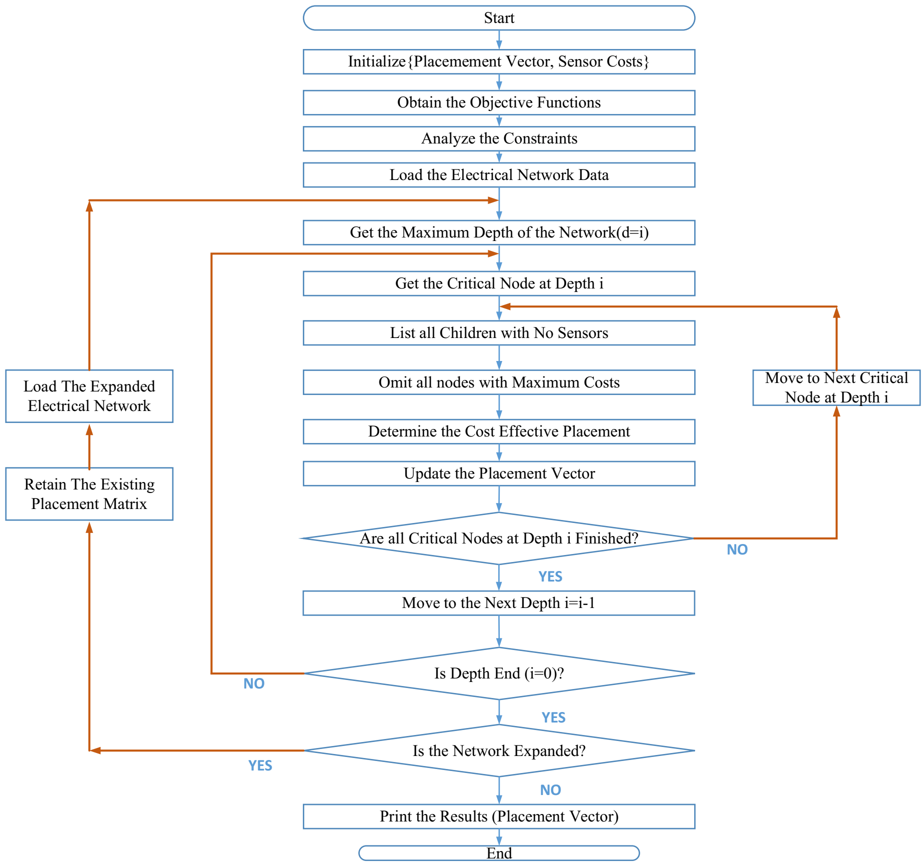

Fig. 5 Algorithm flowchart for the expanded network

Placement results for dynamic case study network

The efficacy of the proposed algorithm was tested for placement in the electrical network of the case study area considering two scenarios. In the first scenario, an electrical radial network of case study area with 79 nodes was considered, and then, the same network was expanded to 97 nodes in order to simulate the changing nature of the SDN.

Figure 11 presents the sensor placement algorithm results for the case study area distribution network with 79 nodes. The results show that three node sensors at node-7, node-10, and node-54 and eleven line sensors were used to observe the entire network. The rest of the branches and nodes without sensors can be accommodated using the rules.

In the case study area network expansion scenarios, new branches at node 7, 11, 31, and 70 were attached to expand the network from 79 to 97 nodes. The algorithm was executed using the expanded network's connection matrix without considering the existing sensors in the original network. Figure 11 presents the sensor placement when the case study network was expanded to 97 nodes.

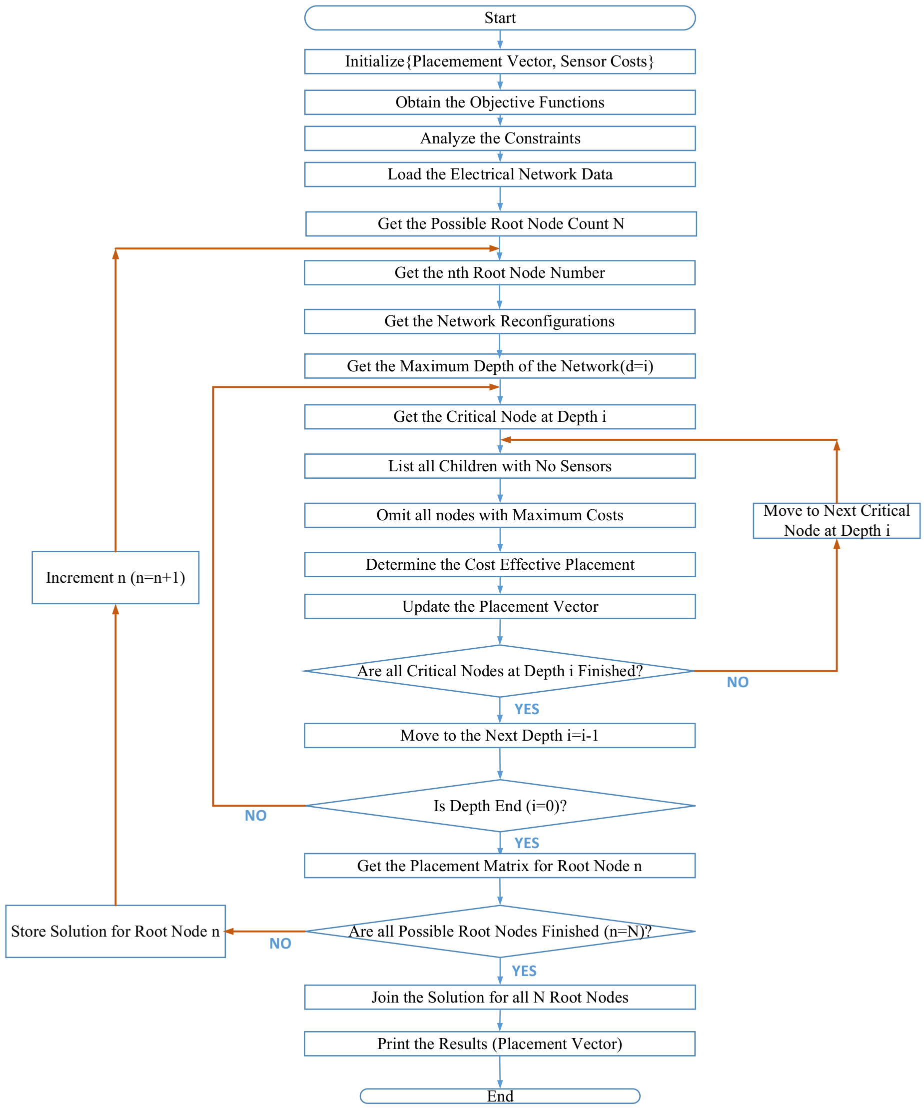

Fig. 6 Algorithm flowchart for root node reconfiguration

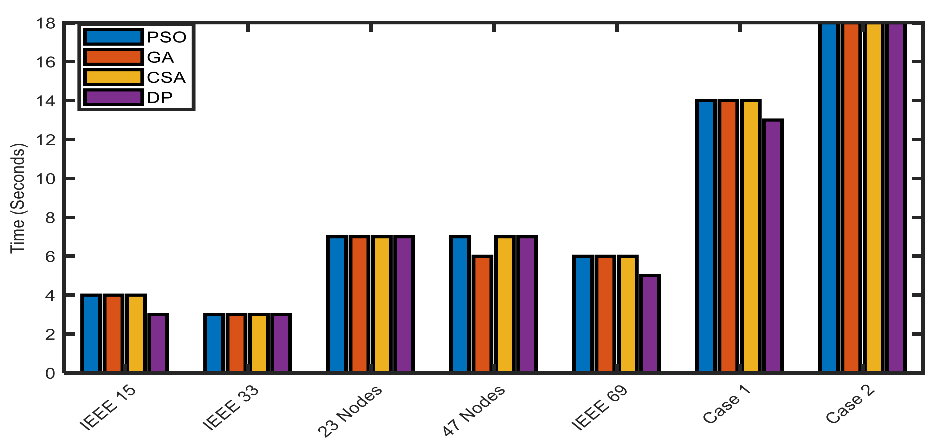

Fig. 7 Number of proposed sensors comparison

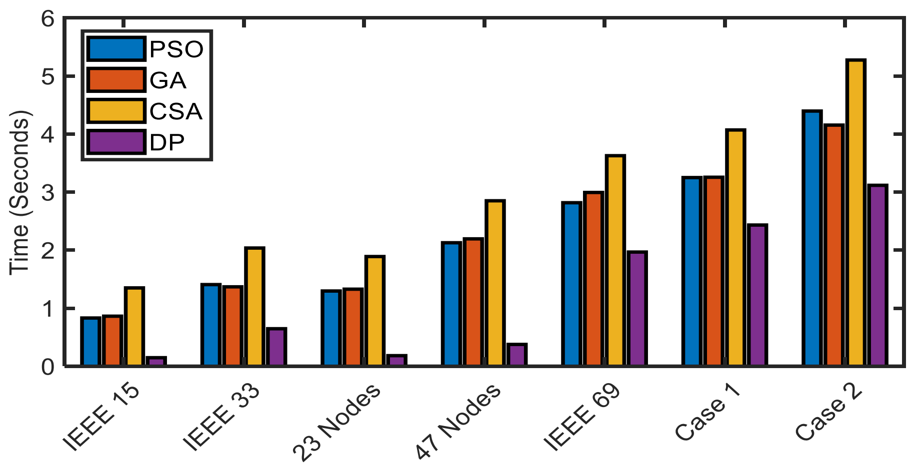

Fig. 8 Convergence time comparison

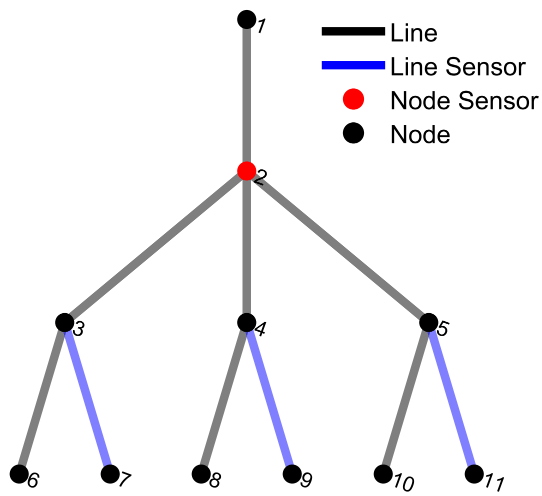

Fig. 9 Sensor placement on 11 node network

Placement results for fixed and reallocated sensor positions

The experiment was conducted to test the performance of the algorithms for fixed and changing sensor positions using the network presented in Fig. 9. The main objective of this experiment was to find optimal placements that reduce placement costs. The objective function is presented in (7), and cost assumption for line sensor is 1 unit and node sensors are 2 units.

$$C = N_n C_n + N_l C_l \tag{7}$$

where C is the total placement cost, N_n is the number of node sensors, C_n is the unit cost of node sensor, N_l is the number of line sensors, and C_l is the unit cost of line sensor.

The fixed sensor experiment was done under assumptions that upon network expansion the available sensors before expansion maintains their positions. The algorithm proposes the position of additional sensors. Changing sensor locations consider that upon

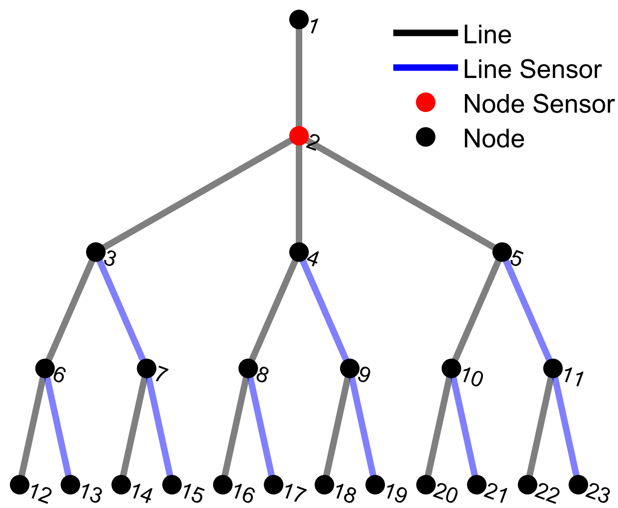

Fig. 10 Sensor placement results on 23 node network

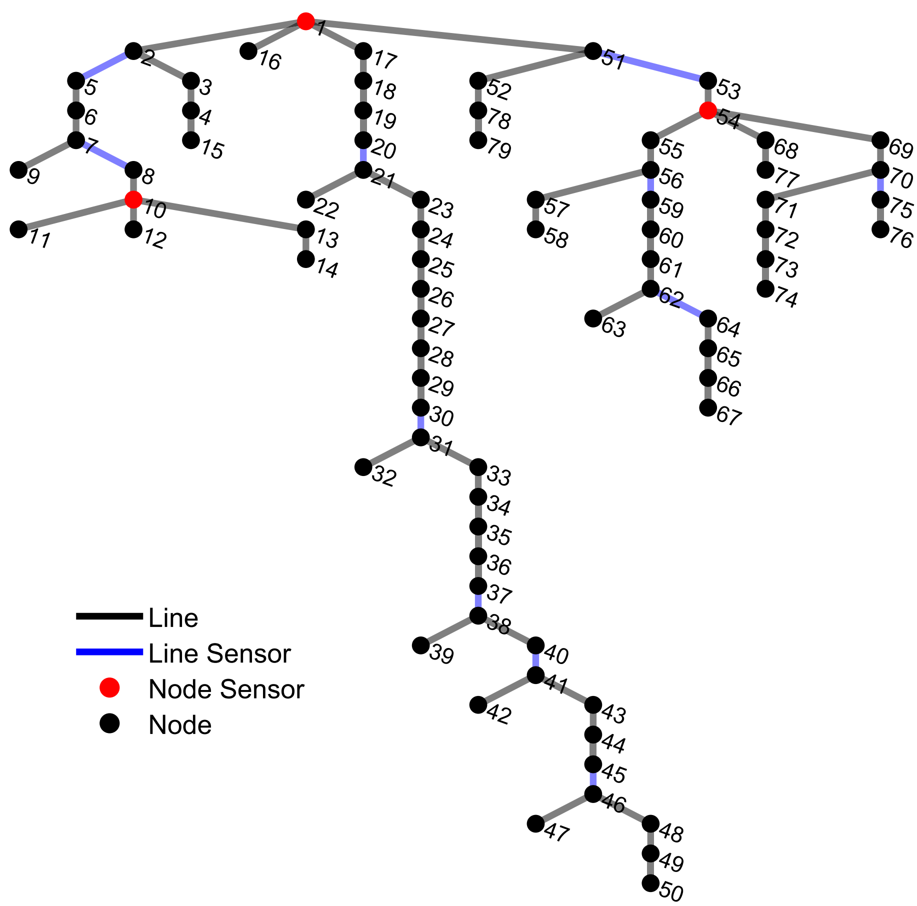

Fig. 11 Sensor placement at the case study area

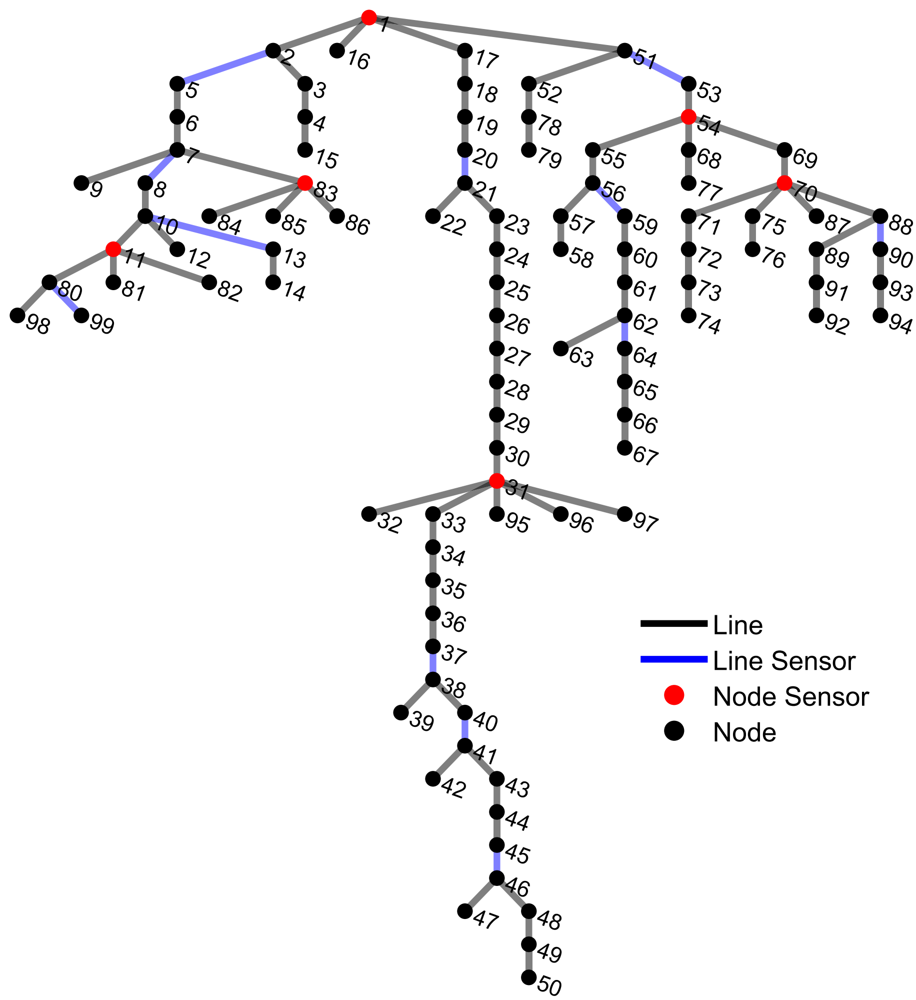

Fig. 12 Sensor placement when the network expanded to 97 nodes

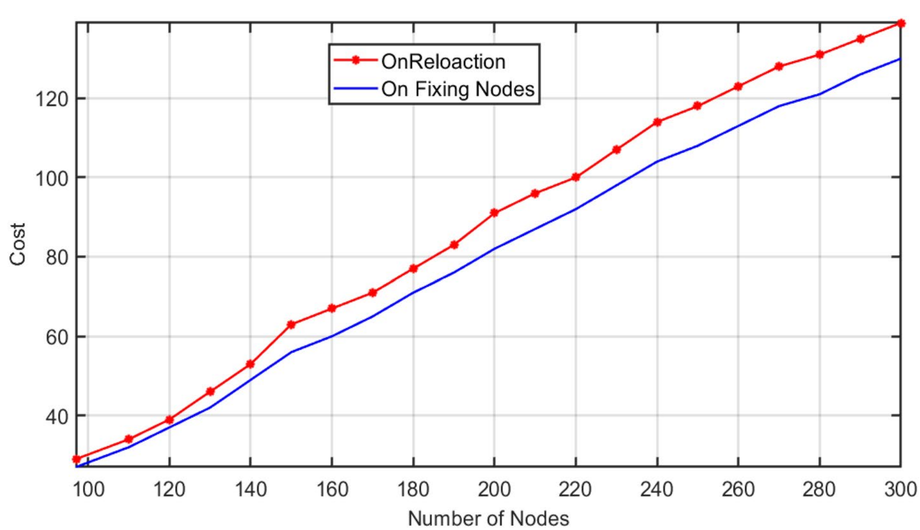

Fig. 13 Comparison table when the sensors are fixed versus relocated

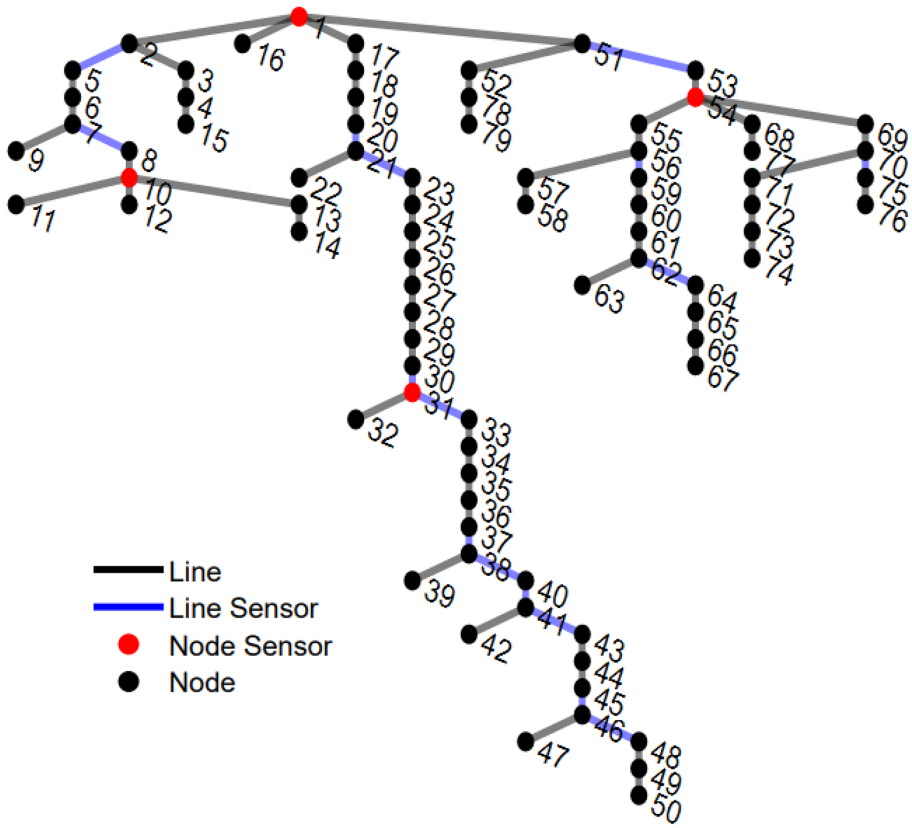

Fig. 14 Sensor placement on network reconfiguration

network expansion location of existing sensors can be changed and additional sensors can be added accordingly.

The first experiment was done with considerations that the locations of the existing sensors can be changed, and the second one was done considering that the existing sensor position was fixed. The results show node sensor number 10 was shifted, and the line sensors 31 and 70 were also shifted when considered the flexibility that the existing sensors can be shifted as shown in Figs. 11 and 12. The total cost when fixing the sensors was 27, and the cost when the sensors can shift was 29. The results show that the cost is low when the sensors are fixed rather than when the sensors are subject to be shifted in the secondary distribution network.

Furthermore, the network was expanded with 10 additional branches randomly on each iteration to visualize its behaviors on network expansions. The costs were recorded considering the scenario when fixing the initial sensors and when relocating the sensors. The sensor nodes were expanded from 79 nodes to 300 nodes, and the results revealed that the cost when a sensor is fixed is lower than when the sensors are relocated. Figure 13 presents the comparison of the cost for fixed and relocated sensors.

The algorithm was tested for inclusion of distributed energy resources (DER) in the electrical secondary distribution network. In the network with DERs, the node with DERs can be considered as root node. In this study, it was assumed that the DERs can be placed on any node. Therefore, the algorithm for placement should include dynamic root node considerations. The algorithm provides an option to choose the potential nodes for the DER insertion, which will be the root nodes. The algorithm then proposes the sensor locations, which will make the network observable whenever the root node changes to any of the chosen locations. Figure 14 presents the proposed sensor locations when the possible root nodes are at nodes 1, 50, and 31. This means that the DER can be inserted in any of the selected nodes, and the same sensor will be able to observe the entire network.

Conclusion

The algorithm for sensor placement was developed using a dynamic programming method that was found to be appropriate compared to the other methods, including PSO, GA, CCSA, and GA. The study revealed that the average convergence time of the proposed method is less than 2 min and keeps on increasing as the network expands. When the algorithm was used to model different networks with varying number of nodes, the results revealed that only 30% of the nodes in a network, need sensors to observe the entire network, hence optimizing the costs. This study also revealed that the cost is optimized when the existing sensor nodes are fixed to their initial locations when the network expands. When the network extends which is the typical scenario in SDN, the model can be deployed to suggest the new sensor locations only in the extended network while retaining the existing ones. The proposed algorithm has also been tested for inclusion of DERs by considering changing root node. The study can be extended to validate the algorithm for faults detection on the real network by ensuring that the sensor nodes are well coordinated to capture faults across the network.

Abbreviations

AMR	Automatic meter readings
CCSA	Chaotic crow search algorithm
CS	Crow search
DER	Distributed energy resources
DMS	Distribution management system
DP	Dynamic programming
GA	Genetic algorithm
ILP	Integer linear programming
KCL	Kirchhoff's current law
PMU	Phasor measurement units
PSO	Particle swarm optimization
SCADA	Supervisory control and data acquisition
SDN	Secondary distribution network
TANESCO	Tanzania Electric Supply Company Limited

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Authors contributions
The idea for this manuscript was proposed by DM and mainly involved in literature review, designing of algorithms, drawings and overall drafting of the manuscript. SK was partly involved in designing and coding of the algorithms and overall arrangement of the manuscript. All authors went through the article and approved the final manuscript for submission. All authors read and approved the final manuscript.

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Declarations

Ethics approval and consent to participate

The manuscript has complied with all ethical considerations and all authors were willing to fully participate.

Consent of publication

The authors of this manuscript approved the publication by the Journal of Electrical Systems and Information Technology.

Competing interests

The authors declare that they have no competing interests.

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