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ORIGINAL PAPER

New Dual Algorithm to Placement the Data Aggregation Point for Smart Grid Meters

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Abstract
The Smart Meter Neighborhood Area Network (SM-NAN), commonly referred to as the last mile network, is a crucial component in enabling communication within the smart grid. This network facilitates the connection between Smart Meters (SMs) and Data Aggregation Points (DAPs), responsible for gathering energy consumption and invoicing data from SMs. The placement of DAPs significantly impacts the distance and transmission lines connecting them to SMs. Our research focuses on optimizing DAP deployment to minimize mean and maximum distances between DAPs and SMs. The paper introduces a system that introduces the concept of network division and develops two techniques to address the DAP placement problem. Through extensive simulations based on actual suburban community topologies, our findings demonstrate the effectiveness of these approaches in reducing the communication gap between DAPs and connected SMs. This research presents promising ideas to enhance the efficiency and performance of the last mile network in the Smart Grid (SG). The performance of two algorithms, $DPCA_{avg}$ and $DPCA_{ws}$, is compared and simulated with varying numbers of DAPs (K = 1, 2, 3, 4, 5, and 6) in the subnetwork, considering maximum and mean distance minimization, as well as the maximum number of hops per path. Results indicate that both $DPCA_{avg}$ and $DPCA_{ws}$ effectively reduce mean and maximum distances between DAPs and SMs, respectively. $DPCA_{avg}$ achieves a maximum distance of 797.3 m, with a mean distance of 345.31 m. In contrast, $DPCA_{ws}$ focuses on minimizing the maximum distance, resulting in a maximum distance of 750.3 m and a mean distance of 423.1 m when the number of DAPs is one (k = 1). $DPCA_{ws}$ demonstrates an awareness of maximum distance and minimizes it, while $DPCA_{avg}$ prioritizes mean distance reduction. Additionally, $DPCA_{ws}$ reduces the maximum number of hops per path, further optimizing the last mile network.

Keywords Data aggregation points · Smart grid · Smart meters · Neighborhood area network · Wireless communication

Abbreviations and acronyms

SM-NAN	Smart Meter Neighborhood Area Network
SMs	Smart Meters
DAPs	Data Aggregation Points
SG	Smart grid
DPCA	DAP Placement Clustering-based Algorithm

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Introduction

The idea of smart cities is being adopted by the governments of many major cities, and they have begun gathering vast amounts of data in order to extract useful information from them. Governments can use this information to raise the living standards and sustainability requirements for their citizens. Lowering expenses and optimizing the use of different energy resources are essential to improving inhabitants' comfort and quality of life [1]. The next-generation power grid, or "smart grid," allows for high-speed and bidirectional, ultra-fast connectivity to improve the reliability, dependability, and efficiency of power resources. SMs are crucial components for a successful SG implementation since they measure precise power use and communicate the gathered data to the grid operator for monitoring of loads and invoice generation. As a result, customers may better manage their power usage since they are aware of their energy usage, and utilities may alter their production to save energy [2]. Referring to Fig. 1, the Advanced Metering Infrastructure (AMI) communication network comprises wide area networks (WANs), home area networks (HANs), and neighbourhood area networks (NANs). This configuration represents a noteworthy blueprint for the Smart Grid (SG), as highlighted in reference [3].

Metering systems, energy from renewables, several laptops and associated plugin components, screens, washers, conditioning units, smart home devices, heating systems, and a variety of electronic appliances are only a few examples of the large range of digital devices connected to the network. These items are all connected via HAN. A concentrator that serves as a WAN gateway is served by NANs, which collect and transmit data from various HANs. Strong data transit between power producing facilities, transmission system substations, many organizations, and numerical HANs is made possible by smart grid WANs. In those networks, a range of communication technologies, including Wi-Fi, Bluetooth, PLC, Zig-Bee, and 3G, are preferred. NANs are crucial for communication in the SG. A NAN frequently includes data DAPs and SMs as its components. Energy use or billing information from smart homes is recorded by SMs. SM data is collected by DAPs and sent to gateways for WANs. Because of its considerable operational options and economical cost, wireless networking is a viable option for NAN.

The efficiency of data exchange between DAPs with SMs for a NAN is significantly impacted by the placement of DAPs. Optimal DAP deployment for a NAN is crucial for a number of reasons, including the communication gap (how far apart DAPs and SMs need to be to exchange data), consumption of energy, transmission rate, and entire latency. Figure 1: two-way communication networks in SG the DAP placement problem is the process of deciding where to put DAPs so that enough acceptable SMs may be deployed to achieve a goal.

The DAP placement problem has received little attention from researchers, and there are few solutions proposed in the published work [4, 5]. This study investigates the use of DAP in NAN as a means of bridging the gap in communication involving DAP and the associated SMs. Splitting this into two sub-problems, minimizing the average and maximum distances, respectively. To minimize the variation in space between DAPs along with SMs, this project's primary purpose is reducing the standard deviation. The maximum distance between DAPs and SMs should be decreased as a secondary goal. In this research, the idea of the "partitioning of networks" method and clustering-based solutions to these two issues are presented. To address the issue of DAP placement, which can be thought of as a network partition problem, a DAP Placement Clustering-based Algorithm (DPCA) is used. The architectural layout of a real suburban neighbourhood will be used in our evaluation of the system's performance. The proposed technique may greatly shorten the distance between the DAP and the connected SMs, as shown in the simulation results.

The following are the key contributions that this study makes:

- The DAP placement challenge in a SM network is formulated as a network division challenge. Both a minimum and maximum distance between DAPs and the connected SMs have been established as goals.

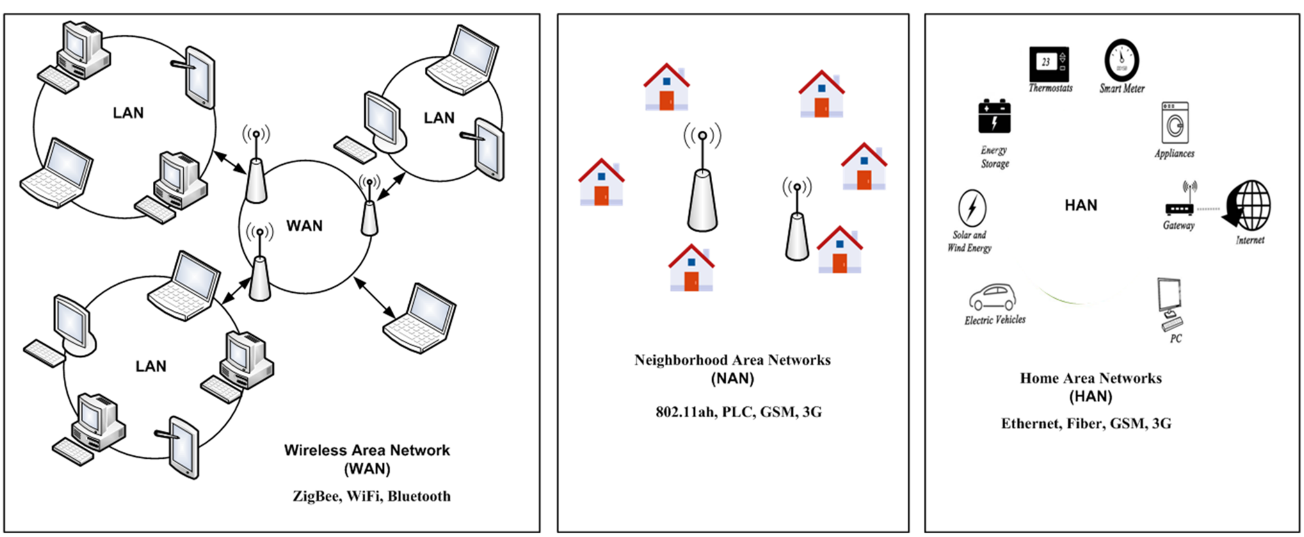


Fig. 1 Two way communication networks in smart grid

- To solve the problem of where to put DAPs, the idea of network partitioning is presented. Exploring the drawbacks of conventional clustering techniques and presenting an alternative that simplifies network partitioning and DAP deployment. Then, to accomplish network segmentation and DAP placement, a clustering-based technique is created.
- The proposed solutions are verified by using a real-world suburban community as the topography. In order to decrease the average and maximum distance between DAPs and associated SMs, the proposed approaches may involve dividing the network through subsection networks and deploying DAPs. Extensive simulations and their results demonstrate this.
- The inability of DAPs and SMs to effectively communicate is a key concern in the DAP placement debate. Potential future directions for the DAP placement problem are presented, along with their associated problems.

The following is the outline for this paper. In Section "Related work", the relevant work is presented. The problem's mathematical formulation is presented in Section "Problem identification". In Section "Algorithms for DAP placement based on clustering", the novel method will be provided. Section "Experimental results" demonstrates the results of our analysis of the solution's performance. Section "Conclusion" concludes the work and suggests further areas of research into the DAP placement problem.

Related Work

As can be seen in Fig. 1, NANs are crucial for an SG as they allow for the connection of LANs and WANs. SMs and DAPs, which collect data from SMs and forward it to WAN gateways, form the backbone of a NAN. In order to optimize the network's communication channels, transmission rate, and consumption of energy, optimal DAP placement is crucial for wireless communications between SMs and DAPs. Therefore, it is essential to consider the ideal locations for DAP placement and to develop plans for integrating DAPs into a NAN. The DAP challenge, which has received interest from both academics and businesses, is the process of placing DAPs in the right places in a network of SMs. In this section, the previous research is previewed and the reason for this particular article is discussed.

The financial impact of DAP deployment is one target of the installation. Costs associated with DAP implementation, consuming energy, and the running period of a network are all factored in to get the full cost of deployment [4]. To reduce the overall cost of DAP installation in a network, the optimal location is analyzed. The solution's limited applicability to real-world systems results from its heavy reliance on the cost function model. It also presumes that SMs only communicate with DAPs via a single hop, which could prove to be the case for low-capacity SMs.

In order to reduce DAP deployment costs while still allowing all meters to reliably connect to a DAP, the authors of [3] propose an alternative approach. The DAP problem is restated in this study as an issue with setting up a set, which is then solved using heuristic techniques. In particular, reliable connections are established in advance using data collected on local characteristics, available networks, antenna heights, and transmission rates. By decomposing the DAP placement problem into smaller, more manageable chunks, reducing the amount of time needed to run the code and the amount of data needed to store the answer.

SG is a large and complex system [6] that includes power generation, transmission, distribution, operations, and administrative activities including metering and billing. Massive volumes of data processing and communication are essential for SG. In order for the SG to be accessible, a number of operations and data exchanges must meet certain time delay requirements [7]. For example, it takes milliseconds for a signal to be generated and sent for preventative measures. Transferring SCADA data quickly is a necessity [8]. According to the findings of [9] and [10], for SG applications involving rapid flaw detection, a propagation latency of 10 to 100 ms is acceptable for a small network.

One must be cautious about the smart grid's privacy protection. With the use of fog computing, Hongyang Li et al. created a privacy protection strategy for outsourcing smart grids that allows for fine-grained, user-characteristic-based privacy-protected data aggregation. The results of the experiment studies show that compared to existing systems, the suggested scheme has reduced transmission delay and less calculation overhead [11]. FedNorm is a revolutionary asynchronous federated learning system for load forecasting using smart meter data, as proposed by Fekri M. et al. FedNorm is an asynchronous federated learning strategy that aggregates updates without waiting for lagging clients, in contrast to conventional synchronous federated learning systems that require all clients to finish local training in each round of aggregation. The tests show that compared to other methods, FedNorm produces greater accuracy and requires fewer communication cycles [12].

Two methods for improving the efficiency of data transmission are compression of data [13–15] and optimization of networks [16, 17]. One of the most used methods for transmitting data across a variety of networks is the shortest distance path, which is popular due to its ability to save time and resources [18, 19].

A comparison was conducted between research attempts to solve the problem of placing aggregation points for meters in a smart grid network. Table 1 presents the comparisons between previous works, from the perspective of methodology, result readings, advantages of each method, and criteria for each approach.

Table 1 A brief comparison of previous DAP techniques

Research paper	Methodology	Results (numerical data)	Advantages	Shortcomings
Lang et al. (2021) [20]	Genetic Algorithm (GA)	Optimal DAP placement, reduced average distance by 25.6%, max distance by 20.3%	Incorporates real-world data, Improved communication efficiency	Limited focus on scalability and network growth
Wang et al. (2017) [21]	Mixed Integer Linear Programming (MILP)	Minimized average delay by 63%, improved energy efficiency by 46%	Addresses delay and energy efficiency simultaneously, Applicable for large-scale networks	Limited exploration of communication constraints
Kong (2017) [22]	GA	Reduced deployment cost by 14%, improved communication efficiency	Incorporates interdependent networks, Addresses cost and communication efficiency	Focus on deployment cost, Limited exploration of other network constraints
Rolim et al. (2017) [23]	Greedy Algorithm	Achieved 7% improvement in average delay, reduced communication cost by 11%	Efficient heuristic approach, Addresses communication and cost trade-offs	Limited exploration of large-scale scenarios, Doesn't consider network growth
Tavasoli et al. (2016) [24]	Mixed Integer Nonlinear Programming (MINLP)	Reduced energy consumption by 16%, improved delay by 32%	Considers hybrid wireless-wired communication, Addresses energy efficiency and delay trade-offs	Doesn't explore scalability and impact of network growth
Rolim et al. (2015) [25]	Particle Swarm Optimization (PSO)	Addressed trade-offs between distances and power loss, improved cost efficiency by 15%	Considers both communication and power network aspects, Multi-objective optimization approach	Limited scalability consideration
Aalamifar et al. (2014) [26]	Genetic Algorithm (GA)	Achieved 10% better results in terms of distance compared to existing methods	Presents a cost-efficient solution, Provides accuracy in DAP placement	Doesn't consider communication constraints

The DAP placement problem in smart grid networks presents multifaceted challenges that demand careful consideration. Determining optimal DAP locations is intricate, involving a delicate balance between coverage, communication range, and network connectivity. The dynamic nature of smart grid networks, characterized by varying energy consumption patterns, adds a layer of complexity to the placement conundrum. Scalability becomes a pressing concern as the smart grid expands, necessitating efficient DAP placement strategies for a growing number of smart meters. Energy efficiency is paramount, requiring algorithms that minimize DAP energy consumption while upholding network performance. Additionally, ensuring reliability and redundancy in data aggregation processes is crucial for the uninterrupted operation of the smart grid. Looking forward, potential future directions for research include the integration of machine learning for adaptive algorithms, real-time optimization strategies, hybrid approaches that combine different optimization techniques, addressing security considerations, exploring integration with renewable energy sources, and investigating the role of edge and fog computing in DAP deployment. Tackling these challenges and exploring these directions promises to advance the efficiency and adaptability of DAP placement in smart grid networks.

This article examines an SM network that is highly sensitive to delays as a means of closing the communication gap between DAPs and their associated SMs. To adequately investigate distance at which SMs can receive signals from DAPs, the problem and conduct research was characterized using two scenarios. For the former case, it is preferable to keep DAPs and SMs as close together as possible. The second is to minimize the space between each DAP and its associated SMs. In this study, the authors introduce the concept of network split to solve the DAP placement issue. In order to minimize the average and maximum distances between DAPs and SMs, the entire network is divided into smaller sub networks for each neighborhood. This study evaluates our methodology by applying it to a real-world suburban setting.

Problem Identification

In this part, the DAP placement problem in a SM-NAN is constructed and a brief introduction to the terms and concepts that are used in this research is provided. To learn more graph terms, consult the book [27].

A NAN can be described as a two-dimensional, undirected, simple graph G = (V, E) with no negative weighted edges, where the set of vertices (V) is the collection of SMs and the edges (E) are the connections between them. SMs have the ability to communicate data directly to a DAP as well as serve as relays for other nodes' messages to be sent into the DAP. A positive value exists for every edge that reflects its cost, such as energy use, distance traveled, traffic congestion, and other factors. Distance serves as the paper's representation of the edge. The vertex and edge primary keys in a graph are indicated by the letters |E| and |V|, respectively. Supposing that SMs' transmission models correspond to disk models. SM connections are symmetrical, and the radio used for transmission is omnidirectional. The communication range is the same for all SMs.

Each SM's communication range is indicated by the disk-based symbol r_c. The SM v_i can link up with v_j if and only if the Geometric distance $\left|v_i - v_j\right| \leq r_c$ for any two separate SMs $v_i, v_j \in$V. The neighbors of v_i are referred to as *Nrc*, and they are all the nodes that are in rc's communication range, i.e. $Nrc\left(v_i\right) = \left\{ v_i : \left|v_i - v_j\right| \leq r_c, v_j \in V \right\}$. Figure 2 shows the communication range and neighbors of the SM v_i. Note that throughout the remainder of the paper, the terms “node” and “SM” are used considered to be synonymous. Graph G is assumed to be a connect graph. Any pair of distinct SMs can interact with one another either directly or through a finite number of intermediary SMs.

Let $V = \{v_i\}_i = 1, \ldots., |V|$ represent a certain suburban neighborhood, where v_i represents the i^{th} SM. A SM's position is indicated by the notation $v_i^l(x_i, y_i)$, where x_i and y_i represent the SM's respective longitude and latitude. DAP placement entails dividing the network G = (V, E) into smaller networks and assigning DAPs to each of those networks. $DAP = \left\{dap_1, \ldots .., dap_k\right\}$, where k represents the overall number of DAPs, is used to denote the collection of DAPs. The number of SMs assigned to the i^{th} DAP is represented by n_i, which equals S_i. The set of SMs assigned to dap_i is defined by $S_i = \left\{s_0, s_1, .., s_{n_i}\right\}$ where $n_i = \left|S_i\right|$. The distance between any two nodes is denoted by the symbol

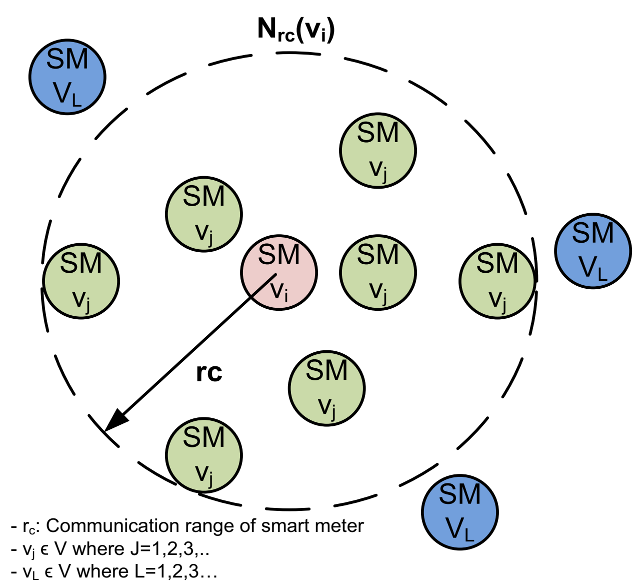


Fig. 2 The communication range and neighbors of the SM v_i

$d(u, v)$ where $(u, v \in V)$. Figure 3 shows that every SM allocate to only one DAP.

Distance is significant in wireless communications [28, 29] because it affects both consumption of energy and route planning. In wireless sensor networks, for instance, data packets should be sent from sensors to the nearest neighbor [30, 31]. Since SMs are a sort of wireless sensor network, it is important that DAPs in a local area network be placed in such a way as to minimize the space between the DAPs and the meters. There are two primary objectives in working to reduce the lag time between DAPs and SMs. The first strategy is known as "average distance minimization," and it works to lessen the distance between SMs and DAPs on average. The second is called worst-case distance minimization, and it works to minimize the maximum potential gap between SMs and DAPs. These two aims are stated in the following terms.

$$D_{avg}\left(P^l\right) = \frac{1}{|V|}\sum\nolimits_{j=1}^{k}\sum\nolimits_{s_i \in S_j} \min d(s_i, dap_j) \tag{1}$$

This equation calculates the average distance reduction for a DAP location P^l. It considers the typical distance between SM s_i and candidate DAP locations dap_j within subnetworks.

$$D_{ws}(P^l) = \min\left\{\max\left\{d(s_i, dap_j)\right\}\right\} \tag{2}$$

This equation determines the worst-case distance minimization for a DAP location P^l. It focuses on the maximum possible separation between SM and candidate DAP locations within subnetworks.

$$\cup_{i=1}^{k} A_i = G(U, V) \tag{3}$$

This equation expresses that the union of subnetworks A_i covers the entire network $G(U, V)$. It ensures comprehensive coverage of the network by the subnetworks, Subnetworks are denoted by $A = \left\{A_i\right\}_{i=1,\dots,k}$

$$A_i \cap A_j = \varnothing, \forall i \neq j, i, j = 1, 2, \dots . \tag{4}$$

Equation (4) stipulates that subnetworks A_i and A_j are disjoint for distinct indices i and j. It ensures that each SM is allocated to a single subnetwork.

$$\varphi\left(A_i\right) = 1, \forall i = 1, 2, \dots ., k \tag{5}$$

Equation (5) signifies that SMs within the same subnetwork A_i should be in close proximity to each other.

$$\varphi\left(A_i \cap A_j\right) = 0, \forall i \neq j, i, j = 1, 2, \dots , k \tag{6}$$

Equation (6) asserts that SMs assigned to distinct subnetworks should be positioned far apart from each other.

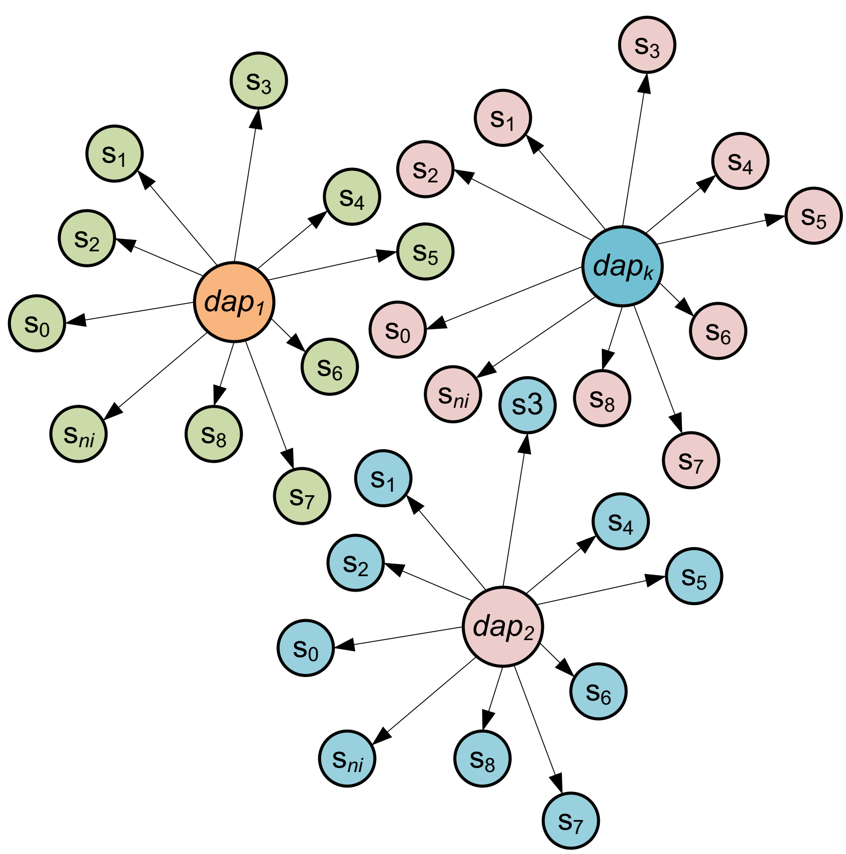


Fig. 3 Shows that SMs allocate to only one DAP

$$SDN_i \text{ is connected network}, \forall i = 1, 2, \ldots, k \quad (7)$$

Equation (7) indicates that each subnetwork SDN_i is a connected network, ensuring direct or mediated communication between its nodes.

$$DAP_i, s_i \in A_i, \forall i = 1, 2, \ldots, k \quad (8)$$

Equation (8) outlines the selection criteria for a DAP (DAP_i) within each subnetwork (A_i). It specifies that both the DAP and associated SMs (s_i) should belong to the same subnetwork.

The DAP placement challenge is similar to the NP-hard facility location problem [32], which calls for heuristic methods [33]. The DAP placement issue is examined, looking for methods of decreasing the distance between DAPs and their associated SMs. To specifically meet the goals outlined in (1) and (2) equations, two clustering methods are created. Additionally, assessing and contrasting how those two objectives will perform and discussing how this has an impact on the DAP placement issue.

The applicability of the proposed system, which involves the utilization of the New Dual Algorithm for localizing DAPs within the SM-NAN, is context-dependent and influenced by various technical, logistical, and environmental factors. These include: network topology, data volume, communication range, network division, algorithm performance, simulation accuracy, resource constraints, regulatory and environmental factors, network growth, integration challenges, and cost-benefit analysis. A proper assessment of these factors and consideration of the system's impact on the efficiency and performance of the smart grid will determine its suitability for implementation.

The proposed system, which employs the New Dual Algorithm for optimizing the placement of DAPs within the SM-NAN, demonstrates strong applicability across a range of technical, logistical, and environmental factors. Through meticulous evaluation of network topology, communication range, data volume, and algorithm performance, the system showcases its adaptability in scenarios where network layout is well-structured and the volume of data generated by smart meters is substantial. By strategically dividing the network into sections for DAP deployment, the system capitalizes on feasible network divisions, further enhancing its practicality. Realistic simulation results contribute to its validity, ensuring accuracy in estimating optimal DAP locations. In addition, the system's scalability accommodates network growth and the integration of new smart meters, supporting its applicability over the long term. While considering regulatory and environmental constraints, the system's flexible algorithmic approach ensures compliance and minimal environmental impact. Overall, with careful attention to cost-benefit analysis and compatibility with existing infrastructure, the system demonstrates its potential to significantly enhance the efficiency and performance of the smart grid, solidifying its applicability as a viable solution for optimized DAP placement (Fig. 4).

Algorithms for DAP Placement Based on Clustering

In this section, further detail will be provided on how to divide a NAN into subnetworks and arrange DAPs in accordance with those subnetworks using clustering methods. Solutions to the DAP placement problem can be taken from the context of clustering algorithms since it is similar to facility location challenges. However, network partition and the DAP placement problem cannot be addressed using conventional clustering techniques, such as K-means. To make things clearer, the term "clustering algorithms" is defined and describes how poorly network architecture is split. The network division and DAP placement will then be carried out using a clustering-based DAP placement technique.

The center and centroid are two essential factors in clustering techniques. To be clear, the initial nodes chosen to run the clustering algorithms are referred to as the “centers”. The centroid is the actual node that clustering algorithms ultimately find. The four key phases of a typical clustering algorithm, such K-means, are as follows:

(1) Create k clusters at random, and give each cluster a single center point.
(2) Use the distance measure to assign nodes to one of the groups.
(3) Update each cluster's centroid.
(4) Continue carrying out steps 2 and 3 until each cluster stays the same.

The following limitations prevent the use of conventional clustering techniques for network partitions. ***First***, it is impossible to determine the distance between two nodes using the distance measure since it is possible that there are no physical linkages along its journey. As shown in Fig. 5, there are 9 SMs from the neighborhood network that search for the shortest route. The path from SM s_4 to SM s_9 is dashed because the Euclidean distance is larger than the transmission range of SMs. The right SMs should be chosen to act as relays to help with communication if the SM transmission range is less than the Euclidean path from s_4 to s_9. For instance, there are three alternative pathways from SMs s_4 to s_9 when the transmission range of the devices is set to 50 m. There are three of them: $r_1 = [4\ 3\ 6\ 7\ 8\ 9]$, $r_2 = [4\ 3\ 2\ 6\ 7\ 8\ 9]$, and $r_3 = [4\ 3\ 2\ 1\ 7\ 8\ 9]$. As r1 possesses the shortest route between SMs 4 and 9, it will be chosen as the final route to determine the separation between those two SMs. On the other hand, because there is

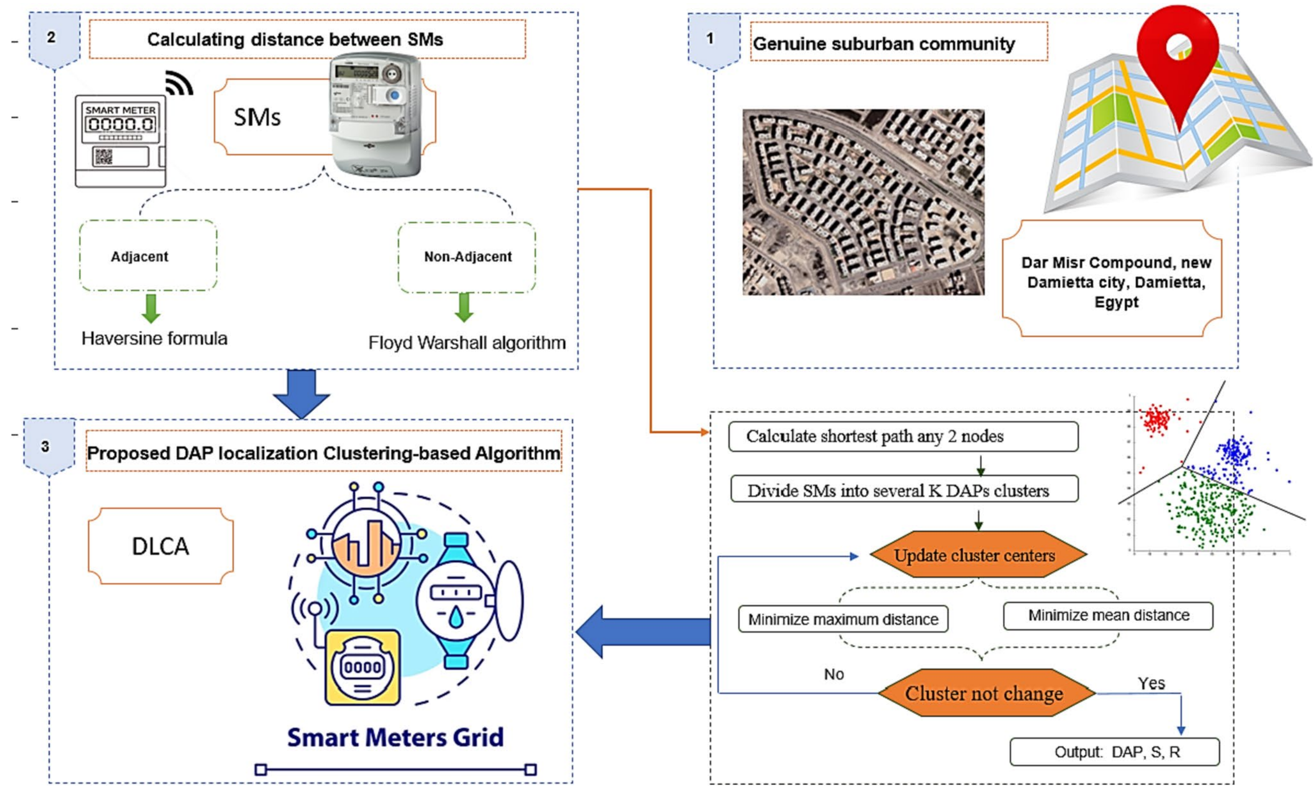


Fig. 4 Proposed DPCA

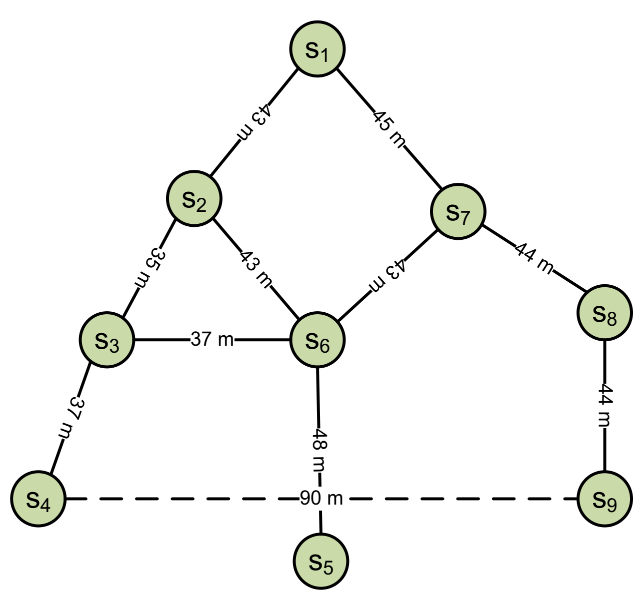


Fig. 5 Demonstration of possible routes among SMs

no accessible route, the direct line from 4 to 9 in Euclidean space is not the optimal way for transmission.

Second, relay SMs are required to send signals from one SM to the DAP owing to the short range of SMs' transmission.

Third, to ensure there are pathways between the centroid and its associated SMs, the centroid, where DAP is put, should be selected from already-existing SMs ($DAP_i \in V$).

In the next paragraphs of this part, the strategies for dealing with those problems will be presented and make suggestions on how to fix the DAP placement issue.

Distance Between Adjacent SMs

v_i's neighbor set is referred to in Section "Problem identification" as $N_{rc}(v_i)$, where rc is the transmission range of v_i. Each SM will have $\left|N_{rc}\left(v_i\right)\right|$ neighbors, also known as neighboring SMs in a NAN, with the provided transmission range (rc). It is expected that each SM's transmission range is long enough to allow communication between any two SMs, either directly or through a finite number of intermediary SMs. Thus, $\left|N_{rc}\left(v_i\right)\right| \geq 1$ for each $v_i \in V$ for a NAN with n SMs. Google Map may be used to retrieve the coordinates of those meteors ($SL = \left\{sl_i\left(x_i, y_i\right)\right\}_{i=1,\ldots,n}$). Any two SMs' separation is indicated by the symbol $d_{hav}(u, v)$, which may be determined using the Haversine formula [33], shown in (9).

$$\Delta lat = \left|y_u - y_v\right|$$

$$\Delta lon = |x_u - x_v|$$

$$a = (\sin(\frac{\Delta lat}{2}))^2 + \cos(y_u) \times \cos(y_v) \times (\sin(\frac{\Delta lon}{2}))^2$$

$$c = 2 \times arctan2(\sqrt{(a)}, \sqrt{(1-a)})$$

$$d_{hav}(u, v) = R \times c \quad (9)$$

where R is radius of the earth (6373 km)

If $d_{hav}(u, v) \leq rc$, SM u (or v) is referred to be an adjacent node of SM v (or u) for any two SMs that are $u, v \in V$. There is no need for relays from other SMs for communication between adjacent SMs. Equation 9 may be used to immediately find the actual separation between two adjacent SMs that can communicate with one another (denoted by $d_{adj}(u, v) = d_{hav}(u, v)$). Relay nodes are necessary for nonadjacent SMs, therefore the real Distance of communication between them (designated

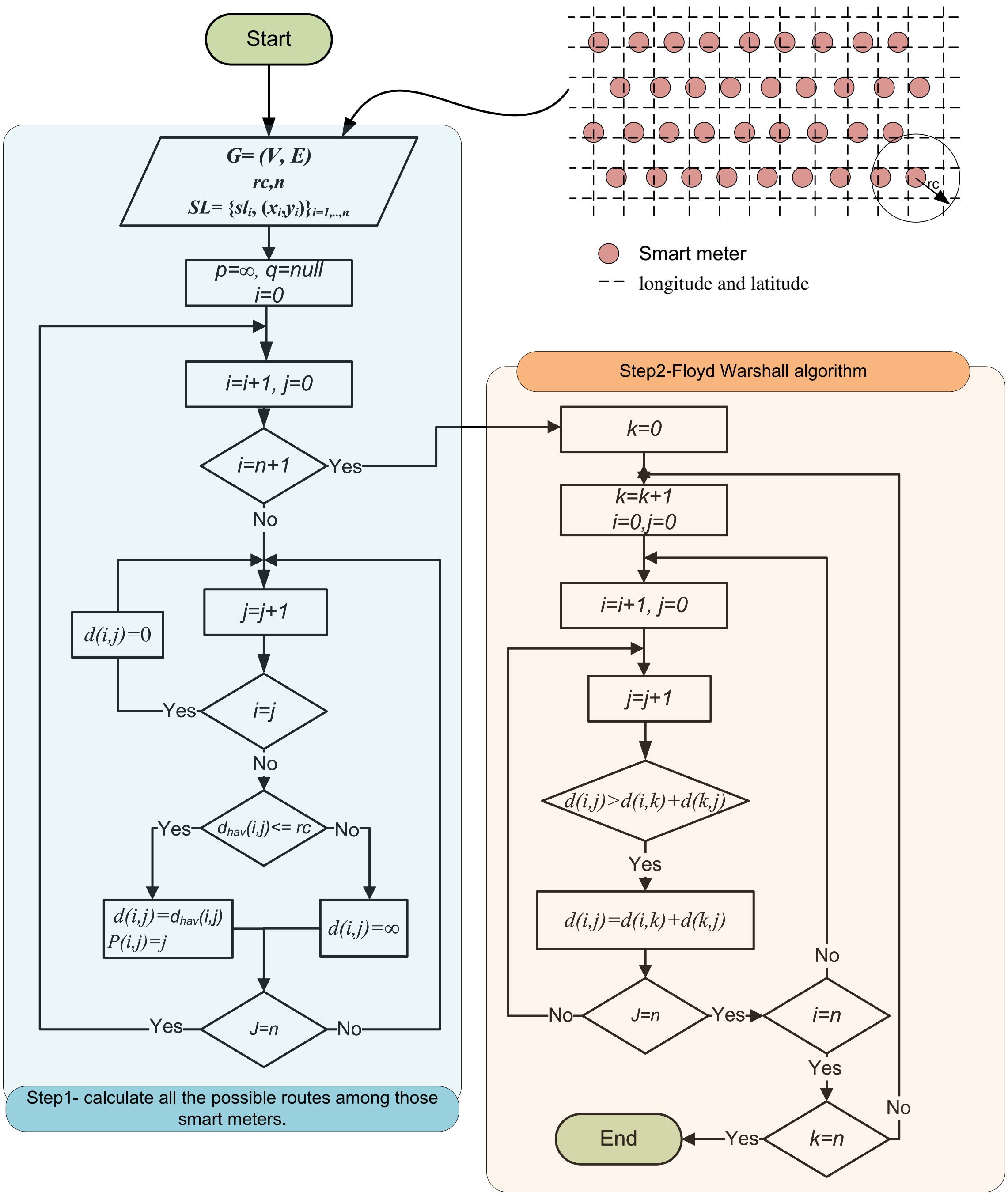


Fig. 6 Flowchart to determine the shortest path between non-adjacent SMs

by the symbol $d_{nonadj} > d_{hav}(u,v)$) is greater than the distance determined by Eq. 9. More complex methods must be used to determine the separation between nonadjacent SMs; these methods will be elaborated upon later.

Distance Between Non-adjacent SMs

Relay nodes are necessary for effective communication among nonadjacent SMs, as discussed in Section "Distance between adjacent SMs". In this part, more details about how to choose relay nodes and determine the best paths for non-adjacent SMs are presented. An additional illustration of why conventional clustering techniques cannot be used in network topology partitioning.

To determine the shortest path between non-adjacent SMs, an algorithm is suggested, which shown in algorithm (1). Figure 6 shows the flowchart of the first and second step of calculating best path between non-adjacent SMs. Calculating every path between those SMs is the first step. The total routes to its nearby SMs are $\left|N_{rc}(v_i)\right|$ for SMs $v_i \in V$. As stated in Section "Distance between adjacent SMs", $\left|N_{rc}(v_i)\right| \geq 1$ indicating that there are many pathways between those SMs. Therefore, choosing the shortest path for each pair of SMs makes sense. This work, in its second step, uses the Floyd Warshall algorithm [34] in particular to determine the shortest path between several options. The Floyd-Warshall method has a $O(n^3)$ complexity, where n is the total number of SMs in a NAN. Floyd Warshall method surpasses other algorithms in terms of simplicity, despite the fact that more effective algorithms may be found in [35].

As shown in Fig. 5, the nine SMs search for the shortest route. The path from SM s_4 to SM s_9 is dashed because the Euclidean distance is larger than the transmission range ***rc*** of SMs. The right SMs should be chosen to act as relays $s_4$ands_9. For instance, there are three alternative pathways: $r_1 = [4\ 3\ 6\ 7\ 8\ 9]$, $r_2 = [4\ 3\ 2\ 6\ 7\ 8\ 9]$, and $r_3 = [4\ 3\ 2\ 1\ 7\ 8\ 9]$. As $\boldsymbol{r_1}$ the shortest distance between points 4 and 9, it will be chosen as the final route to determine the separation relating to those two SMs. The flow chart in Fig. 5, will cancel the direct path from s_4 to s_9 and it cannot be used as the real communication route. On the other hand, because there is no accessible route, the Euclidean path from s_4 to s_9 cannot be used as the real communication route.

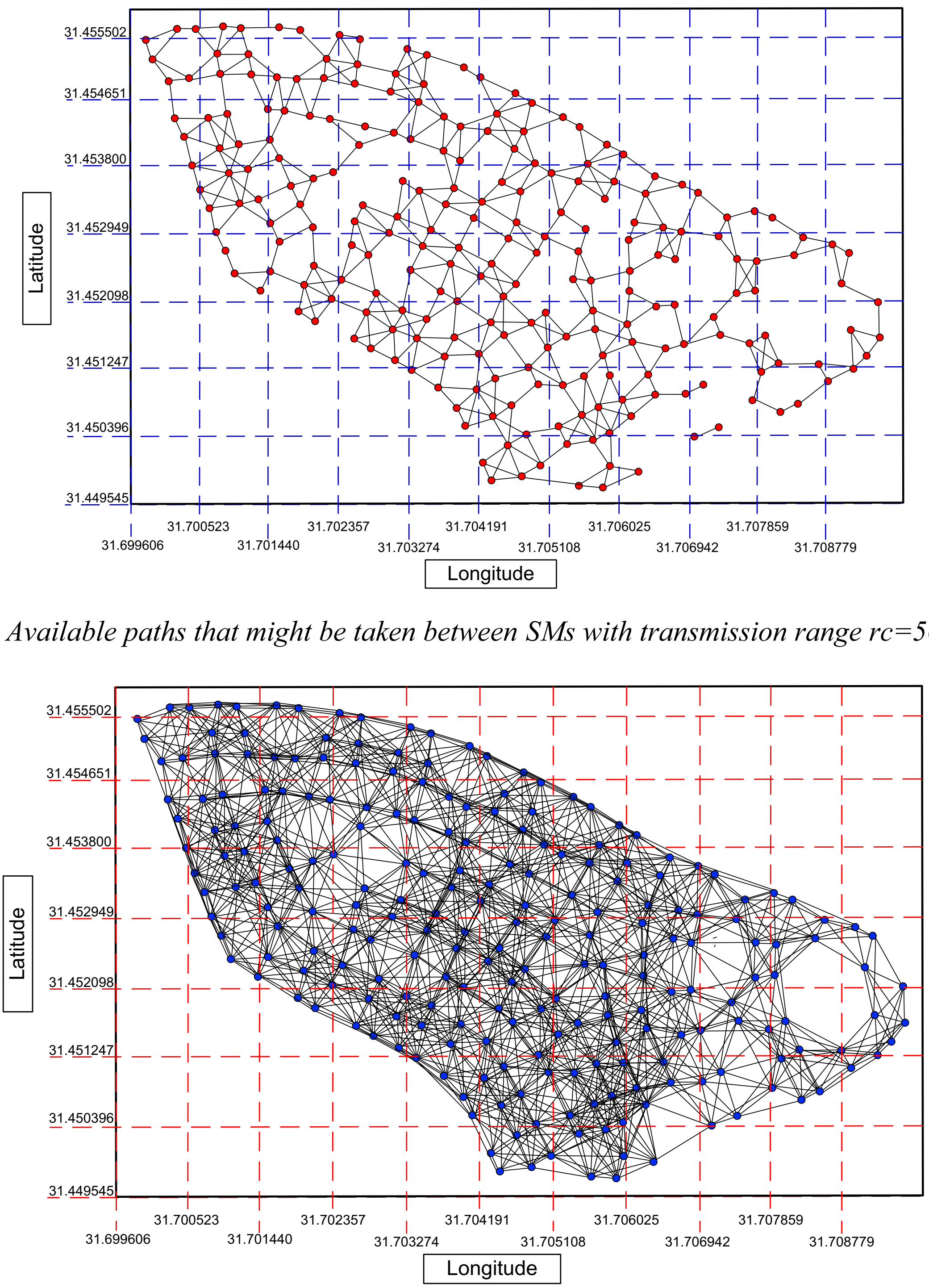
Fig. 7 A real suburban neighborhood selected from Dar Misr Compound, new Damietta city, Damietta, Egypt

Algorithm 1 Determine the shortest path between non-adjacent smart meters

**** Input:***
- ***G= (V, E)*** a given suburban area network
- ***SL=*** $\{sl_i, (x_i, y_i)\}_{i=1,\dots,n}$ the coordinator of SMs in suburban area network *G*. Where $n = |V|$, representing the number of SMs in the network.
- ***rc***, transmission range of SMs in the suburban area network, Suppose the transmission range of all SMs is the same.
- ***n***, number of SMs in the network.

**** Output:***
(1) ***d***: *nxn* matrix of minimum distance among SMs in ***G***.
(2) ***p***: *nxn* matrix of shortest paths among SMs in ***G***.

**** Steps:***
```
- start with d= ∞, p= null
- for i=1 to n
     for j=1 to n
        if i=j then
           d(i,j)=0
           continue// escape to next iteration
        elseif d_hav(i,j) ≤ rc then
           d(i,j) = d_hav(i,j)
           P(i,j)=j
        else
           d(i,j) = ∞
     end
  end
        //Floyd Warshall method
- for k=1 to n
     For i=1 to n
        for j=1 to n
           if d(i,j)>d(i,k)+d(k,j) then
              d(i,j)= d(i,k)+d(k,j)
              p(i,j)=p(i,k)
           end
        end
     end
  end
-end
```



(a) Available paths that might be taken between SMs with transmission range rc=50m

(b) Available paths that might be taken between SMs with transmission range rc=100m

Fig. 8 The possible routes in the given NAN with different transmission ranges

Table 2 Shows the simulation parameters

Simulation name	Qualnet 5.1
Number of SM nodes	230
Transmission ranges	rc = 50 m, rc = 100 m
Simulation time	10 s
SM location	Dar Misr Compound, new Damietta city, Damietta, Egypt
Simulation date	10/2022

Algorithm for DAP Placement Based on Clustering

In Sections "Distance between adjacent SMs" and "Distance between non-adjacent SMs", the preliminary work for distance computation is discussed in more detail. The clustering-based DAP Placement Algorithm (DPCA) will be provided in this section to divide a NAN into subnetworks and deploy DAPs in the proper places. Algorithm (2) presents the related algorithm.

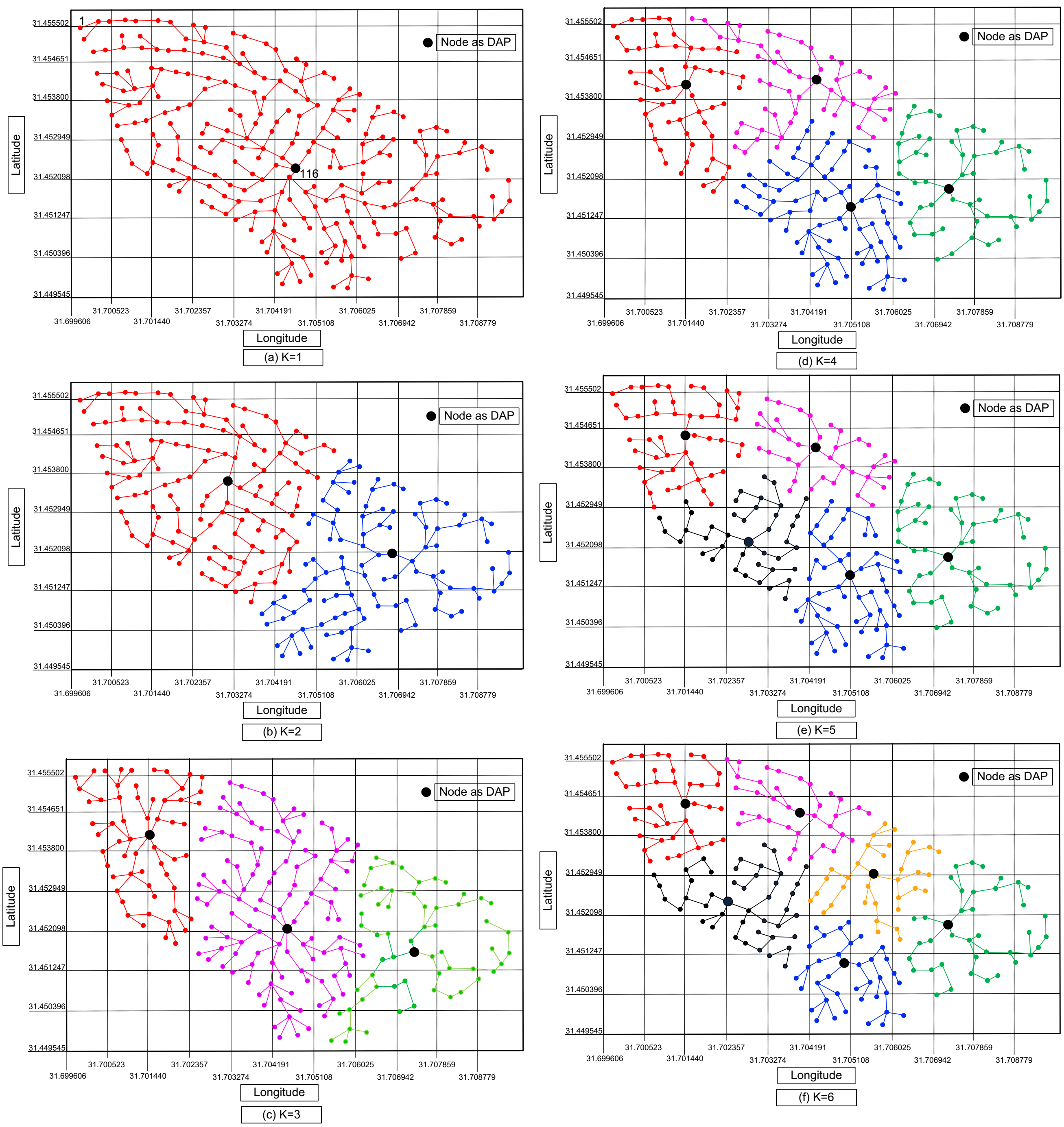


Fig. 9 Simulate DPCA$_{avg}$ for demonstrate of DAP placement and associated routes

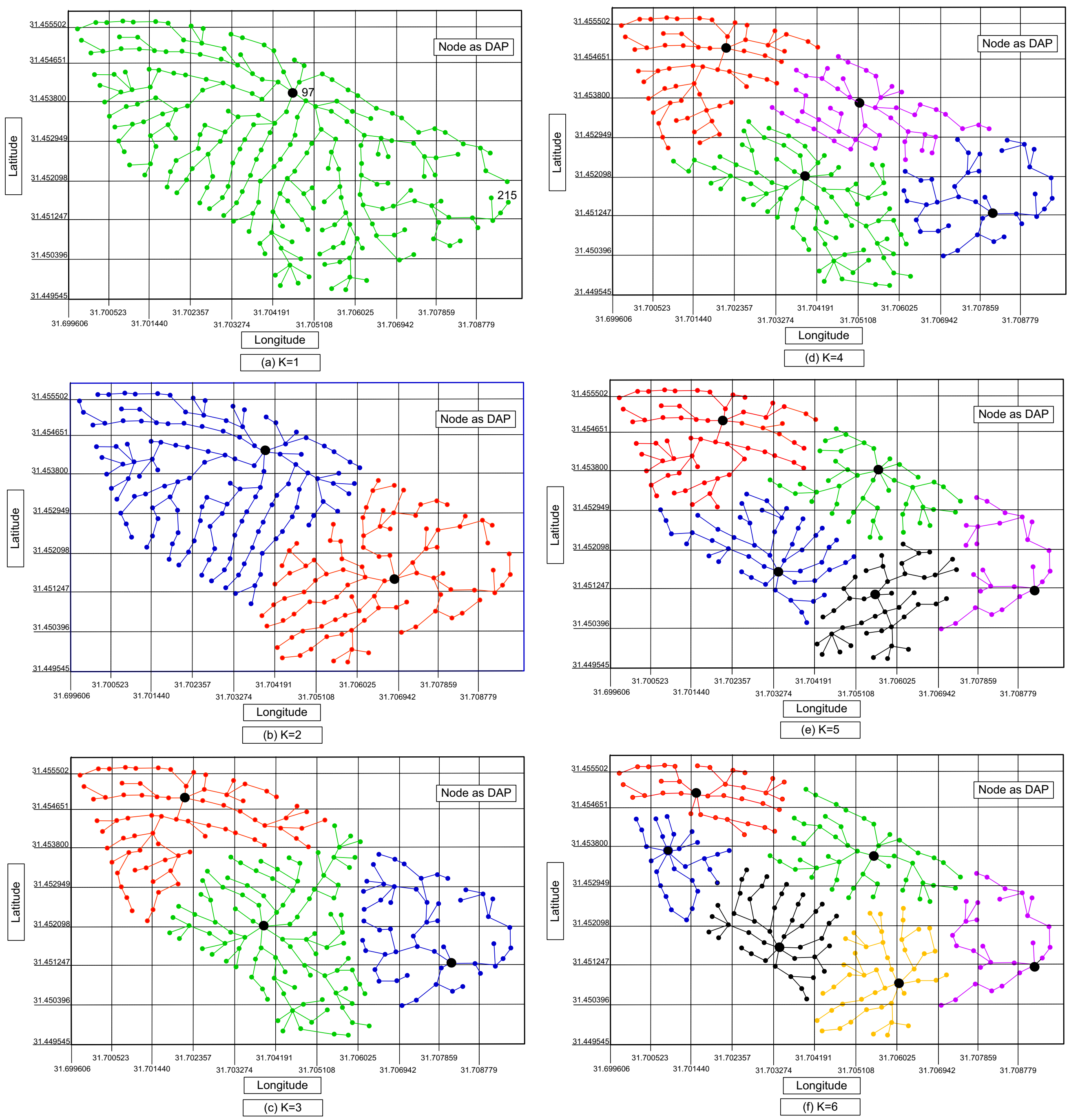


Fig. 10 Simulate DPCA$_{ws}$ for demonstrate of DAP placement and associated routes

The inputs to *DPCA (k)* are the number of SMs (n) in a particular network, their coordinates ($SL = \{sl_i(x_i, y_i)\}_{i=1,\dots,n}$), transmission range ($rc$), and the number of *DAPs*. The identification of *DAPs,* the set of SM clusters (S), and the routing set for each subnetwork (R) are all part of DPCA's output. The whole explanation for each step is provided below.

Algorithm 2 DAP Placement Clustering-based Algorithm (DPCA)

**** Input:***
- ***K:*** *the number of DAPs*
- ***SL*** $= \{sl_i, (x_i, y_i)\}_{i=1,\dots,n}$ the coordinator of SMs in suburban area network G
  Where $n = |V|$, representing the number of SMs in the network.
- ***rc***, transmission range of SMs in the suburban area Network, assume all SMs have the same transmission range.
- ***n***, number of SMs in the network.

**** Output:***
(1) $DAP=\{dap_i\}_{i=1,\dots,k}$:*the instance of DAP*
(2) $S=\{s_i\}_{i=1,\dots,k}$: the set of SM in each DAP
(3) $R=\{r_i\}_{i=1,\dots,k}$:the routing paths of each subnetwork

**** Steps:***
1- Calculate *d(i,j), p(i,j)* which are the shortest path distance between any 2 nodes.
2- Initialize random k centers ($C=\{c_i\}_{i=1,\dots,k}$)selecting from SMs S
3- Distribute the SMs $s_i(s_i \in S)$ to one of the k cluster using the relation:
$$v \in c_i, if\ d(v, c_i) < d(v, c_j), \forall i, j \in \{1,2,\dots,k\}, i \neq j$$
4- Update centroid $C' = \{c_i\}_{i=1,\dots,k}$:
 - Minimize mean distance as in eq (1)
$$c_i' = v_m, if \frac{1}{n'} \sum d(v_m, v) = minimum, \quad \frac{1}{n'} = cluster\ size, \forall\ m, v \in cluster_i, \quad i = \{1,2,..,k\}$$
 - Minimize maximum distance as in eq(2):
$$c_i' = v_m, if max\{d(v_m, v)\} = minimum, \forall m, v \in cluster_i, i = \{1,2,..,k\}$$
5- Repeat step 3,4 until no change in each cluster
6- Save C' to DAP, $\{cluster_i\}_{i=\{1,2,..,k\}}$ to S, and routing paths to R
7- end

Using Algorithm 2, each pair of SMs' shortest possible route among all of their potential paths is determined as the first step of DPCA. Step 2: To initiate the clustering, ***k*** is the number of SMs picked at random from the network to act as cluster center. SMs are divided up into several clusters in Step 3 according to their shortest paths to the ***k*** centers. SMs are specifically assigned to the cluster that is closest to the ***k*** centers. Since fresh SMs are distributed to those ***k*** clusters throughout each cycle, the cluster center needs to be updated for each cluster. Step 4 entails this procedure, which uses two approaches to deal with various goals. The new cluster center is created in step 4 (1) with the intention of reducing the average distance between cluster members and the center. In contrast, step 4 (2), which seeks to lessen the maximum outward distance that cluster members can be from the cluster's center, achieves the worst-case scenario. The steps of steps 3 and 4 are repeated until each cluster does not change, as shown in step 5. In Step 6, the algorithm's output is acquired. Due to the Floyd-Warshall algorithm's difficulty, Algorithm 2 has an $O(n^3)$ complexity.

Table 3 Shows the maximum distance, average distance, and max number of hops per path for $DPCA_{avg}$

Number of DAP	Maximum distance	Average distance	Max number of hops/ path
K = 1	797.3	345.3	21
K = 2	707.77	332.1	13
K = 3	629	297.5	11
K = 4	397.1	265.3	9
K = 5	344.6	246.6	9
K = 6	332.1	225.2	8

Table 4 Shows the maximum distance, average distance, and max number of hops per path for $DPCA_{cw}$

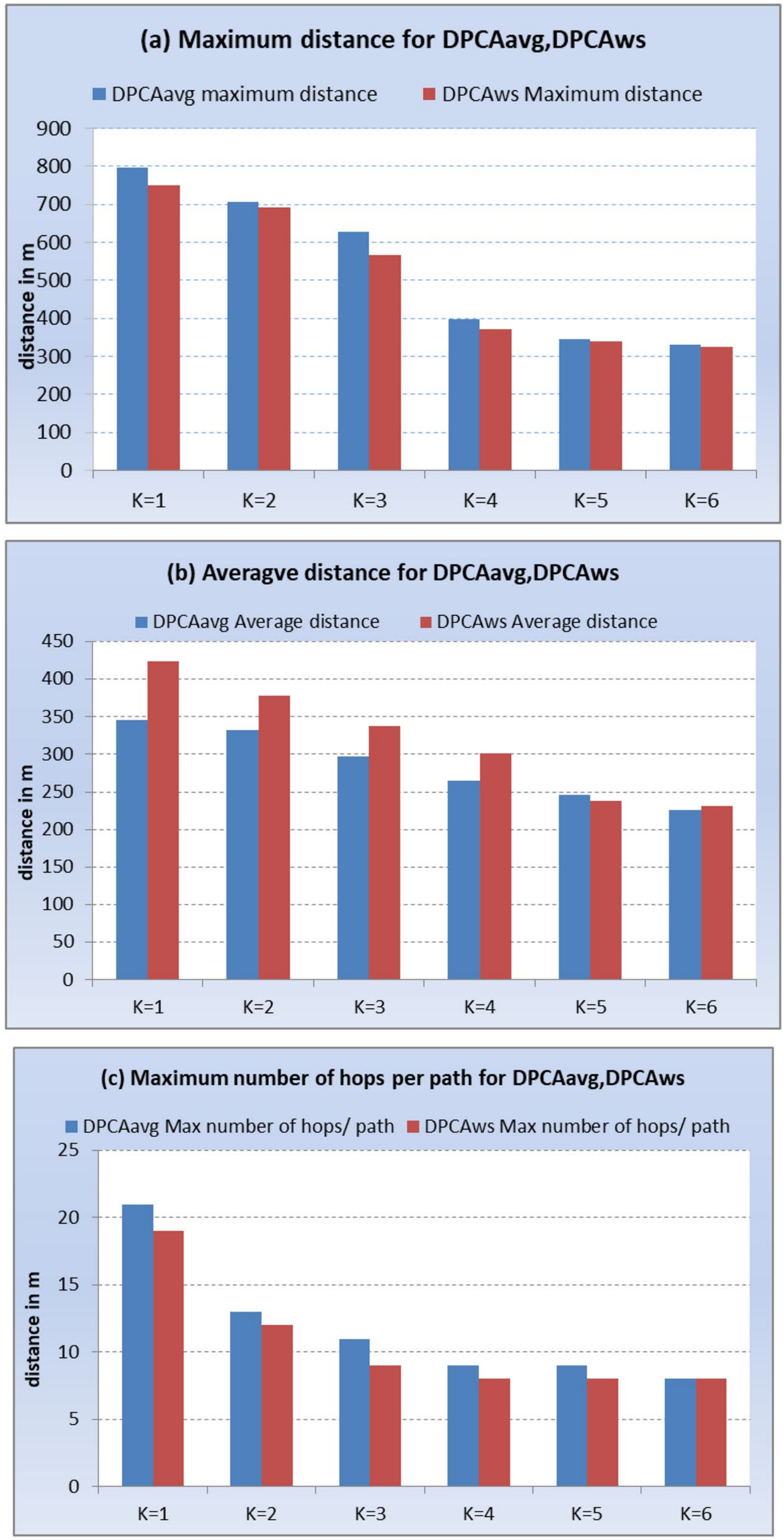
Number of DAP	Maximum distance	Average distance	Max number of hops/ path
K = 1	750.3	423.1	19
K = 2	690.6	377.7	12
K = 3	567.5	337.2	9
K = 4	370.8	301.2	8
K = 5	338.3	237.9	8
K = 6	325.1	231.3	8

Experimental Results

In this section, the network partitioning and DAP placement results shows that DPCA has produced and assess its effectiveness in terms of distance reduction. The NAN in Fig. 7 is based on a genuine suburban community in *Dar Misr Compound, new Damietta city, Damietta, Egypt.*

The Google Map may be used to acquire the coordinates (longitude and latitude) of homes in a NAN, as covered in Section "Algorithm for DAP placement based on clustering". Be aware that many wireless communication technologies, including Zigbee, WiFi, WiMax, cellular networks, etc., have been proposed for use in NANs [6, 36]. The primary goal of this paper is not to defend a particular communication technology. Instead, focus more on the wireless transmission range that could be relevant to one or more protocols because

Fig. 11 Maximum, average distance, and maximum hops per path for the $DPCA_{avg}$ and $DPCA_{ws}$



of the following fact, which highlights how important it is for SM communications. If the transmission range is too limited, SMs will stop communicating with the remaining network and lose connectivity. As a result, communications in this NAN are not successful. To ensure there is at least one path from all SMs to the DAPs, a sufficient transmission range is crucial. Going quickly through the impact of wireless transmission range on SM communications. Next, a detailed illustration of the positioning of the DAP and the network division follows. The performance in terms of distance attained by DPCA will next be assessed in contrast to the average and maximum distance minimizations.

The Transmission Range's Impact on SM Communications

As previously noted, successful communication between SMs and DAPs depends on the wireless transmission range. The SMs' wireless transmission range and how it affects their capacity to communicate will be described in this section. Figure 8a and b show the outcomes of the simulation on *Qualnet simulation software* with 230 SMs.

When the transmission range is set to 100 m, Fig. 8a shows every path that might be taken between SMs. Some SMs, such as those on top, can be seen to be isolated from the NAN, which suggests that such meters will ultimately lose contact with other SMs connected to the NAN. In addition, Fig. 8b shows that when the transmission range is raised to 100 m, all meters are connected to one another over at least one path. The placements of the DAPs and accompanying routes will be chosen using the proposed DPCA in the simulations that follow, which are based on Fig. 8b. Table 2 shows the simulation parameters in Qualnet software [37].

DAP Placement Achieved by DPCA and the Associated Routes

It is suggested that *DPCA* carry out network partitioning and DAP deployment in Section "Algorithm for DAP placement based on clustering". In reality, *DPCA* is made up of two algorithms, $DPCA_{avg}$ and $DPCA_{ws}$, which are used to accomplish two distinct goals that are outlined in Section "Problem identification". In particular, $DPCA_{avg}$ aims to reduce the average distance between DAPs and SMs. The maximum distance between DAPs and the connected SMs is what $DPCA_{ws}$ seeks to reduce. This section presents and contrasts the DAP placement outcomes obtained using $DPCA_{avg}$ and $DPCA_{ws}$, respectively.

Figure 9 shows the DAP placement and related routes that $DPCA_{avg}$ and $DPCA_{ws}$, respectively, were able to achieve. It is evident that the $DPCA_{avg}$ and $DPCA_{ws}$ provide various DAP placement outcomes. The DAP is found to prefer being positioned in the middle of the subnetworks, which is consistent with $DPCA_{avg}$*'s* goal of reducing the average distance between DAPs and SMs. $DPCA_{avg}$ is simulated using different numbers of DAPs (K = 1, 2, 3, 4, 5 and 6) in the subnetwork. In particular, when just one DAP is placed in the network (K = 1), node 116 is chosen as the site of the DAP because it has the shortest sum distance to all other SMs, as shown in Fig. 9a. The longest distance in the network is 797.3 m, which separates the DAP (node 116) from (node 1). 345.31 m is the average distance between DAP and other SMs. Additionally, the shortest paths among all feasible routes—the best routes—from all of the SMs to the DAP are shown.

Figure 10, illustrates the $DPCA_{ws}$*'* DAP placement outcomes. When compared to $DPCA_{avg}$, $DPCA_{ws}$ attempts to reduce the maximum distance between DAPs and SMs therefore, the DAP is more likely to be installed in a position where that distance is reduced. In particular, as shown in Fig. 10a, node 97—which has the shortest distance to other SMs—is where DAP was located using $DPCA_{ws}$. The largest distance between DAP and other network nodes is 750.3 m, which is the distance between nodes 215 and 97. When compared to $DPCA_{avg}$, $DPCA_{ws}$ considerably reduces the maximum distance, as can be seen.

Comparison of $DPCA_{avg}$ and $DPCA_{ws}$

The performance of both algorithms, $DPCA_{avg}$ and $DPCA_{ws}$, is compared in this subsection with regard to maximum, average distance minimization, and maximum

Table 5 Shows comparison of the proposed system with other work

Research paper	Methodology	Advantages	Shortcomings
Wang et al. (2018) [38]	MILP	Considers different scenarios and objectives, Provides various solution approaches	Assumes uniform distribution of meters
Gallardo et al. (2021) [39]	Clustering Algorithm-based Planning	Addresses clustering-based planning, Considers reliability and efficiency	Focus on advanced metering infrastructure, Limited exploration of communication constraints
Wu, Xiaofeng, et al. (2022) [40]	ant colony optimization based end-to-end data collection strategy	improve the network lifetime of wireless sensor network	Constrains in data collection and scalability
Current work	k-means based DPCA	Scalability, Enhanced Efficiency, Cost-Effectiveness	Needs to address more case studies

numbers of hops per path. $DPCA_{avg}$ is simulated using different number of DAPs (K = 1, 2, 3, 4, 5 and 6) in the subnetwork. Table 3, shows the longest distance, average distance, and maximum number of hops per path for each value of K. As shown in Table 3 the maximum, average distance, and maximum hops per path decrease with increasing number of DAPs.

$DPCA_{ws}$ is simulated using different numbers of DAPs (K = 1, 2, 3, 4, 5 and 6) in the subnetwork. Table 4, shows the longest distance, maximum distance, and maximum number of hops per path for each value of K.

The difference between the DAP placement outcomes in Figs. 9 and 10 reflects the distinct optimization goals of $DPCA_{avg}$ and $DPCA_{ws}$. While $DPCA_{avg}$ prioritizes average distance reduction, $DPCA_{ws}$ focuses on minimizing the maximum distance. This results in diverse spatial configurations that align with the respective objectives of each algorithm.

However, when the number of DAP is one (k = 1), $DPCA_{ws}'$ average distance was 423.1 m, which is more than 77 m longer than $DPCA_{avg}$'s result. These examples demonstrate the effectiveness of the suggested algorithms $DPCA_{avg}$ and $DPCA_{ws}$ in reducing the average and maximum distances between DAPs and SMs, respectively. Figure 11 shows the charts for maximum, average distance, and maximum hops per path for the $DPCA_{avg}$ and $DPCA_{ws}$. As shown in Fig. 11a, the maximum distance between the DAPs and meters in the network is for $DPCA_{ws}$ less than the maximum distance in $DPCA_{avg}$. This means that the $DPCA_{ws}$ aware of the maximum distance and minimize the maximum distance than $DPCA_{avg}$. As shown in Fig. 11b, the average distance between the DAPs and meters in the network is for $DPCA_{avg}$ less than the average distance in $DPCA_{ws}$. This means that the $DPCA_{avg}$ aware of the average distance and minimize the average distance more than the $DPCA_{ws}$. As shown in Fig. 11c, the maximum number of hops in the *DPCAws* is less than the maximum number of hops in the $DPCA_{avg}$. This means that the $DPCA_{ws}$ minimize the maximum distance by reducing the number of hops per path (Table 5).

Conclusion

In this study, the primary objective was to optimize the placement of DAPs in a SM-NAN to minimize the distance between DAPs and the connected SMs. To achieve this, two key distance reduction targets: the minimum average distance and the minimum maximum distance were presented. A novel approach was presented, called network partition, which involves dividing the network into subnetworks and strategically deploying one DAP in each subnetwork at an optimal location.

Real suburban area simulations were conducted to assess the performance of the proposed method. The results demonstrated that the proposed approach significantly reduced the distance between DAPs and the connected SMs, offering promising improvements in the network's overall efficiency.

However, despite these advancements, several challenges remain to be addressed before the practical implementation of DAP deployments in the smart grid. These challenges include scalability, resource constraints, and potential interference in densely populated areas. It is believed that addressing these issues in future research will pave the way for successful and widespread DAP deployments in the smart grid, ultimately enhancing the overall performance and reliability of the last mile network.

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Declarations

Ethical Approval No human and/ or animal studies. So, no ethical approval.

Competing Interests Always applicable and includes interests of a financial or personal nature.

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