Optimal Placement of UDAP in Advanced Metering Infrastructure for Smart Metering of Electrical Energy Based on Graph Theory

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Abstract: This paper presents an algorithm to optimize the deployment of hubs for smart energy metering based on the Internet of Things. A georeferenced scenario is proposed in which each user must connect to a concentrator, either directly or through another user, minimizing the resources required to achieve connectivity. Consequently, to carry out the optimization, the minimum spanning tree between devices is found, in which the maximum connection distance and the capacity of the hubs are limited. Additionally, this work seeks to achieve a scalable algorithm applicable to any georeferenced scenario to be simulated. The main contribution of this work is an IoT-based smart metering architecture that optimizes resources and adapts to a scenario that changes or integrates more users to the energy metering network without losing the connectivity of the initial users. As a result of the application of the algorithm, a scenario route map is generated. The scenario’s parameters include the number of hops in the network, the optimal number of concentrators and their geographical location, the average number of hops, and the total distance of the path, among others. In this project, a georeferenced urban scenario was considered in which residential areas coexist with intelligent buildings. The scenario has growth stages in which the algorithm is applied, and in each one, the optimal route map is generated.

Keywords: advanced metering infrastructure; electrical network; graph theory; minimum spanning tree; scalability; optimization

1. Introduction

The increasing use of smart grids has demanded that new metering technologies be developed to meet the communication needs of the grid. In this context, smart meters, as a part of the advanced metering infrastructure (AMI), currently have different types of communication, and the interaction between them is a critical factor for optimal network management [1]. Communication networks can be home area networks (HANs) with a range of tens of meters, neighbourhood area networks (NANs) covering an area of hundreds of meters, or wide area networks (WANs) covering an area of hundreds of meters, or wide area networks (WANs) with coverage of tens of kilometers [2].

The Internet of Things has been a central part of advanced metering infrastructure, providing new wireless communication technologies known as low power wide area networks (LPWANs). Among the most common types of communication used by AMI are LoRa (low power wide range), WiFi, ZigBee (IEEE 802.15.4), SigFox, NB-IoT (narrowband IoT), LTE, and other cellular networks [3]. All the technologies must coexist in the same environment. Other studies on this coexistence have been carried out in [4–10], in which the parameters of each technology and how they influence each other are evaluated.

In the present work, an optimization model of the number of universal data aggregation points (UDAPs) or concentrators necessary to achieve coverage of all smart meters
(SMs) is carried out. The algorithm considers a restriction on coverage ratio and the capacity of the UDAPs. The simulation uses a georeferenced scenario in which the gradual installation of smart meters (SMs) is considered to develop a scalable algorithm. In Figure 1, a simplified scheme of this work is shown. The simulation scenario corresponds to an urban area composed of smart buildings equipped with advanced energy metering systems; in fact, each house is a user with an SM connected to a concentrator or another nearby SM, according to the restrictions defined in the algorithm. In the same way, residential areas that coexist in the same environment are considered.

**MOTIVATION**
Optimal deployment of UDAPs for Smart Metering based on IoT
Minimise the Cost of Resources

**METHOD**
Openstreetmap
Matlab
Greedy - Dijkstra

Ratio and Capacity constraints

UDAP deployment based on IoT

**ANALYSIS**
Capacity - Coverage - Flows
Minimum Spanning Tree

Multi - Hop
Latency
Path Distance

Figure 1. Proposed algorithm for optimal UDAP deployment.

Previous studies on clustering users around a concentrator for intelligent energy metering have evaluated algorithms with randomized solutions using k-means [11–15]. However, the present work exposes the need to obtain a solution that not only clusters but also allows control of the number of hops or the maximum hops required for the data to reach the concentrator from an electric energy meter. The innovation is based on minimizing the number of hops, building a controlled minimum spanning tree, and minimizing the number of concentrators needed to cover all sensors [16,17].

Consequently, simulations were carried out considering smart meter radio connections between 10 and 100 m. This simulates an urban scenario that does not always have a line of sight between the equipment, as is the case in practice. In this context, we worked with the connection ranges of technologies such as ZigBee, Z-Wave, and WiFi, which have the smallest ranges of coverage, as summarized in Table 1.
Table 1. Characteristics of Common Technologies in IoT-based infrastructure.

<table>
<thead>
<tr>
<th>Feature</th>
<th>LoRa</th>
<th>SigFox</th>
<th>ZigBee</th>
<th>Z-Wave</th>
<th>Wifi</th>
<th>NB-IoT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interference Tolerance</td>
<td>Very High</td>
<td>Very High</td>
<td>High</td>
<td>High</td>
<td>Medium</td>
<td>Low</td>
</tr>
<tr>
<td>Sensibility</td>
<td>−168 dBm</td>
<td>−126 dBm</td>
<td>2.4 GHz band: −85 dBm</td>
<td>2.4 GHz band: −85 dBm</td>
<td>−94 dBm to −71 dBm</td>
<td>−141 dBm</td>
</tr>
<tr>
<td>Modulation</td>
<td>CSS</td>
<td>BPSK</td>
<td>OQPSK and BPSK</td>
<td>OQPSK and BPSK</td>
<td>OFDMA, OFDM, QAM</td>
<td>QPSK</td>
</tr>
<tr>
<td>Energy Consumption</td>
<td>Low: 2 mW</td>
<td>Medium: 158–500 mW</td>
<td>Low: 1 mW</td>
<td>Low: 1 mW</td>
<td>High: 1 W</td>
<td>Medium: 710–840 mW</td>
</tr>
<tr>
<td>Span</td>
<td>Urban: 5 km Rural: 20 km</td>
<td>Urban: 10 km Rural: 40 km</td>
<td>10 m to 75 m</td>
<td>Up to 100 m</td>
<td>wifiA(802.11a): 10 m to 70 m</td>
<td>Urban: 1 km Rural: 10 km</td>
</tr>
<tr>
<td>Work Frequency</td>
<td>America: 915 MHz</td>
<td>Europe: 868 MHz and 868 MHz</td>
<td>America: 915 MHz</td>
<td>Europe: 868.40/868.42/869.85 MHz</td>
<td>wifiA(802.11a): 5 GHz</td>
<td>wifiB(802.11b): 2.4 GHz</td>
</tr>
<tr>
<td></td>
<td>Europe: 868 MHz and 868 MHz Rest of the world: 902 MHz and 928 MHz</td>
<td>Europe: 868 MHz Rest of the world: 2.4 GHz</td>
<td>America: 908.4/908.42/916 MHz</td>
<td></td>
<td></td>
<td>licenced bands</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>250 kHz and 125 kHz</td>
<td>100 Hz</td>
<td>2 MHz</td>
<td>300 kHz and 400 kHz</td>
<td>22 MHz</td>
<td>195 kHz</td>
</tr>
<tr>
<td>Baud Rate</td>
<td>0.3 to 50 kbps</td>
<td>100 bps</td>
<td>40 to 250 kbps</td>
<td>9.6 to 100 kbps</td>
<td>wifiB(802.11b): 11 Mbps</td>
<td>200 kbps</td>
</tr>
<tr>
<td>Battery Lifetime</td>
<td>&gt;10 years</td>
<td>&gt;14 years</td>
<td>up to 10 years</td>
<td>up to 5 years</td>
<td>5 to 10 years</td>
<td>&gt;10 years</td>
</tr>
</tbody>
</table>
Urban, suburban, or rural scenarios require the inclusion of user considerations and feasible sites to place a concentrator, which directly influence the cost of implementation. On the other hand, energy consumption depends on the technology used. However, it is necessary to rely on a technology with a minimum cost per unit of energy consumption, and it is also essential to consider the cost increase for the multiple concentrators required to achieve full coverage of the smart meters. In contrast to previous studies concerned with delay and energy consumption [18,19], this paper presents a situation that is closer to reality, moving from basic research to applied research that proposes and recommends a tool to allow electric utilities to deploy wireless resources more efficiently to achieve smart metering at the lowest cost. Future work could consider georeferenced scenarios, delay, and energy consumption. The deployment of microgrids in suburban and rural areas is an opportunity to deploy smart metering infrastructure. Electric distribution companies are requesting guidance on the on-site deployment of telecommunication resources to ensure service and coverage. Previous studies include this issue at the level of a review of the state of the art and current methodologies [20,21].

Considering multi-hopping as a constraint reduces the communication delay by avoiding indiscriminate hopping until a concentrator is reached. Previous studies have commented on the importance of considering multi-hopping as an option to guarantee the sending and arrival of information from the sensor to the concentrator [22,23]. Additionally, incorporating graph theory to solve a routing problem by controlling the multi-hop adjacency matrix allows the least-cost paths to be evaluated and ensures that the constraint on the maximum number of hops is maintained throughout the routing process [24,25].

Considering a literature review of theoretical work on methods of achieving a smart metering infrastructure for electric energy [21], the present work notes as a contribution the application of an algorithm in a georeferenced environment that controls the number of hops and additionally evaluates a low-cost route in terms of wireless resources, considering the lowest number of concentrators. This paper proposes a wireless communications network that collects information that can later be evaluated, analyzed, or even encrypted. Currently, the deployment of wireless sensors is not a trivial problem, requiring fast action for deployment but also for ensuring that the information reaches the destination. In addition, the proposed network must be scalable and resilient, considering increases in sensors and the routing of the network with the new resources deployed. Artificial intelligence techniques are currently attempting to make the first advances to be applied to real scenarios; however, the application focuses on the security and management of the collected information. As a result of an efficient and reliable communication network, the smart metering infrastructure will be able to fulfill its objective of being used to analyze the collected data and determine the energy demand response and management [20]. The inclusion of microgrids in suburban and rural areas presupposes a need for a network capable of adapting technologies and achieving the objective of metering electricity in a given area; for this reason, evaluating georeferenced environments makes this a relevant proposal.

2. Related Work

Studies on optimizing the location of UDAPs (universal data aggregation points) have been carried out in the literature. Consequently, in studies such as [11–13,15,26,27], solutions are proposed based on the problems of distance, network clustering, or latency. The constraints considered are the transmission latency and the number of hops on the link. The proposed solutions employ modified clustering algorithms based on k-means, c-means, and mean shift, and solutions using the Lloyd algorithm or the minimization of the number of hops [28,29].

Other authors evaluate clustering algorithms [30,31] and propose solutions to network partitioning and architecture, respectively. This is done by clusterization through self-aggregation maps and clustering optimization by a fuzzy c-means algorithm. On the other hand, in [32,33], data routing is studied, and it is stated that the problem is the network architecture and the data collection mode. In this case, solutions are proposed by optimizing
the number of UDAPs and their location, and implementing a new data collection scheme, considering feasibility, costs, network capacity, and energy consumption.

The authors also address the communication of the equipment, and they identify the network architecture, connection reliability, and event reporting as problems to be solved. These authors propose to solve the problem using a propagation tree [34–36], minimization of the number of hops [36,37], and a column generation algorithm [38].

The minimum spanning tree algorithm is also proposed to solve problems in network architecture [36,37,39], as well as optimized network clusterization [40]. Energy consumption is also a topic widely studied by the scientific community; studies such as [31,40–44] propose solutions to the energy consumption of SMs and UDAPs through optimal network clusterization, aggregation tree algorithms, minimization of the number of hops, and optimization of information routing, proposing scalable models with restrictions on cost, capacity, energy consumption, and the number of hops.

Genetic algorithms are among the optimization algorithms currently proposed by authors. In this sense, ref. [45] proposes optimization with genetic algorithms to obtain the optimal route and minimize the end-to-end delay in transmission. Another study [46] was carried out using fuzzy inference systems to maximize the profit generated by the exchange of energy in the network under a time-of-use policy.

Data routing is another topic that has been widely discussed, and studies such as [33,37,39–43] propose solutions to this problem by clustering the network, minimizing the distance, and proposing heuristic models that optimize the data collection mode of the AMIs, to avoid data loss, latency in the network, or network saturation.

From the literature analyzed in the bibliometric analysis and other sources that generate research content, it can be intuited that the way forward for optimizing the number of concentrators is an optimal clusterization of the network to reduce latency problems, capacity, costs, and energy consumption.

At the local level, ref. [47] proposes an algorithm for the routing of UDAPs based on a minimum spanning tree algorithm, considering coverage and capacity restrictions in the concentrators. On the other hand, in [48], a summary is presented that integrates the actors, processes, and functionalities associated with smart metering and everything related to the benefit of using these technologies.

In this study, we propose to optimize the deployment of concentrators (UDAPs) considering the scalability of the scenario, which most authors in the literature do not consider. In this way, the algorithm can be adapted to any duly characterized georeferenced scenario. In addition, the developed algorithm presents the possibility of grouping the capacity restrictions of the UDAPs and the connection distance of the SMs, limiting the number of hops allowed in the network. Although these restrictions are considered in the investigated literature, they are considered individually. Instead, in this work, these three restrictions are considered simultaneously. Finally, the proposed solution presents a link route based on the optimal deployment of concentrators without falling into solutions that involve dividing the network into sectors or grouping smart meters in a single cluster. A comparison between the work presented and some of the related work is outlined in Table 2.

The main challenge associated with the correct location of data aggregation points is ensuring the delivery of bidirectional information to the distribution companies in charge of demand response and the management of service outages and reconnections. The fidelity of communication through events or alarms may take a different route in the quest to form a resilient communications network [38].

Furthermore, to ensure the observability of the wireless communications system that serves smart metering, constant monitoring of the communications link is controlled and defined by the frequency with which the electric company requires information from each supply, which varies between 7 and 15 min, or can even be every 30 min. However, readings can also be taken at the beginning and end of each month when there is no information
required or problems in the network, since each smart meter has an information storage capacity of up to three months as a backup [32].

Table 2. Summary of papers related to sizing and georeferenced deployment of UDAPs.

<table>
<thead>
<tr>
<th>Scientific Paper</th>
<th>Problem Constraints</th>
<th>Proposal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Author</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wang et al., 2016 [12]</td>
<td>✠ ✠ ✠ ✠ ✠ ✠ ✠ ✠ ✠</td>
<td></td>
</tr>
<tr>
<td>Chen et al., 2017 [35]</td>
<td>✠ ✠ ✠</td>
<td></td>
</tr>
<tr>
<td>Wang et al., 2017 [15]</td>
<td>✠ ✠ ✠ ✠ ✠ ✠ ✠ ✠ ✠</td>
<td></td>
</tr>
<tr>
<td>Wang et al., 2018 [11]</td>
<td>✠ ✠ ✠ ✠</td>
<td></td>
</tr>
<tr>
<td>Mehrjoo et al., 2018 [23]</td>
<td>✠ ✠ ✠</td>
<td></td>
</tr>
<tr>
<td>Rhim et al., 2018 [22]</td>
<td>✠ ✠ ✠ ✠</td>
<td></td>
</tr>
<tr>
<td>Kiedrowski et al., 2021[24]</td>
<td>✠ ✠ ✠</td>
<td></td>
</tr>
<tr>
<td>Gallardo et al., 2021 [16]</td>
<td>✠ ✠ ✠</td>
<td></td>
</tr>
<tr>
<td>Wu et al., 2022 [25]</td>
<td>✠ ✠ ✠ ✠ ✠ ✠ ✠</td>
<td></td>
</tr>
<tr>
<td>Current Work</td>
<td>✠ ✠ ✠ ✠ ✠ ✠ ✠</td>
<td></td>
</tr>
</tbody>
</table>

The number of data aggregation points per cluster will be variable, depending on the population increase of electricity supplies in a defined area, which implies that the network must guarantee the site’s coverage and ensure that the data reaches the central office of an electric company [49].

Controlling the number of hops allows the latency due to very long delays in sending information between smart meters and data aggregation points to be counteracted, which becomes a benefit for distribution companies and thus provides a reliable metering solution. Delays in the network have been modeled and simulated in previous studies by the same authors, identifying appropriate times for sending information and proposals to the network operator [50].

According to the temporality of the transmission of information, previous work warns of an opportunistic business model and thus minimizes the impact of the energy consumption of the communications network, considering the use of a virtual mobile operator.

3. Problem Formulation

Previous work has shown that it is not sufficient to optimize SM communication based on device distance or network clustering alone in smart metering infrastructure.

To address this problem, the present work proposes to optimize the deployment of hubs, considering the capacity of the UDAPs and the location of the SMs without neglecting the number of hops.
3.1. Proposed Strategy and Methodology

A smart metering system design methodology is proposed to optimize the deployment of concentrators. The proposed scenario is an urban area, with coexisting smart buildings with advanced energy metering systems and residential areas with smart meters for each user. The parameters of the technologies considered for the algorithm’s evaluation are the coverage distance and the multi-hop connection between devices. SM radio connection of 10 to 100 m is considered in an urban scenario. With the variation of the coverage radius, the lack of a line of sight between the SM and UDAP is considered, reducing the connection distance for the devices. Additionally, UDAPs are considered to have a capacity ranging from 5 to 30 UDAPs or SMs connected simultaneously.

Moreover, the scenario considers four stages, to obtain metrics based on population growth, increasing the number of users in the network and obtaining the optimal hub deployment and routing tree for each stage.

A georeferenced scenario is proposed, in which the latitude and longitude coordinates of the smart meters are used. Additionally, candidate sites where the concentrators could be positioned are considered, taking the intersections of the streets in the scenario as a reference. Furthermore, the proposed algorithm considers scalability, adapting to the changing needs of the scenario and the fact that a wireless network is used; it can recalculate the optimal route in the presence of new smart meters integrated into the network. Consequently, to simulate this adaptability of the algorithm, the simulation of four growth stages of the scenario under analysis was carried out. In this work, although the transmission rate of the equipment was considered, the energy consumption of each node was not.

Figure 2 shows a schematic of the process to be followed to determine the optimal deployment of the hubs, taking into account the constraints mentioned above.

![Methodological flowchart for the optimal UDAP deployment.](image-url)

Considering graph theory as the basis of the algorithm, \( G = (V, E) \) represents a connectivity matrix \( G \), where \( V \) represents the vertices or edges (smart meters and data aggregation points) and \( E \) represents the wireless communication links. Then, in the optimization process, it is necessary to start from a set of candidate sites where a UDAP could be located, which could be places where a street lighting mast is situated. In this way, the georeferenced coordinates of smart meters and candidate sites are entered into the model, and from the optimization model, the process of minimizing the UDAPs, the routing of the wireless network, and the routing of the UDAPs are determined.
The objective function is:

$$\begin{align*}
\text{min:} & \quad \sum_{i=1}^{N+M+K} d_{ij}X_{ij}; \quad \forall (i, j) \in E \\
\text{min:} & \quad \sum_{i=1}^{M} Z_{ij}; \quad \forall i \in S \\
\text{subject to:} & \quad \sum_{h=1}^{H} \psi_i \leq N_{\text{hops max}}, \quad \forall h \in H \\
& \quad \sum_{j=1}^{M} X_{i,j} \leq CapZ_i, \quad \forall i \in S
\end{align*}$$

Equation (1) presents the objective function that minimizes the path as a function of the maximum distance allowed by the modeled wireless technology and its corresponding link between a smart meter and a data aggregation point. Equation (2) shows the minimum number of data aggregation points in the modeling discarded from the set of candidate sites. Equation (3) expresses the total number of multi-hops that the route can generate for each part of a tree. It is referred to as a constraint on the maximum number of hop assignments in the model. This is done to reduce the communication latency occurring when there is an indiscriminate number of hops. Equation (4) presents the maximum number of links that can exist at a data aggregation point, considering the capacity of the concentrator device.

3.2. Proposed Solution

The algorithm developed in this work proposes the optimal deployment of concentrators. The algorithm consists of three main stages: the characterization of the scenario, a pre-selection of the optimal location of the UDAPs, and the final optimization of the scenario with a minimum spanning tree deployment. The method used to arrive at the optimum deployment is explained in this section. Table 3 presents the nomenclature used in the process.

In the scenario characterization stage, all the geographical information of the study area is taken into account. In this study, the geographical distribution of users, the location of smart meters, the possible locations of concentrators, and the locations of base stations are taken into account.

The distance matrix is calculated using the geographical coordinates of the points mentioned above to calculate the distance between each SM, UDAP, and BS. The most suitable candidate sites will initially be selected based on the maximum distance selected for the simulation. Using this information, the optimization of the hub deployment will be carried out.

Once the scenario characterization has been carried out, the geographical coordinates of the devices, together with the UDAP capacity selected for the exercise and the maximum connection distance of the SMs according to their technology, are the input variables of Algorithm 1. The first step of this algorithm involves making a pre-selection of the candidate UDAPs, employing the function “calc_base_tree”, which is described in Algorithm 2. Step 3 involves finding the matrix of distances, connectivity, and cost.
Table 3. General notation for model and algorithms.

<table>
<thead>
<tr>
<th>Nomenclature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>(d_{i,j})</td>
<td>Distances matrix (SM–UDAP–BS)</td>
</tr>
<tr>
<td>(X_{i,j})</td>
<td>Wireless links</td>
</tr>
<tr>
<td>(\text{CapU})</td>
<td>UDAPs maximum capacity</td>
</tr>
<tr>
<td>(Z_i)</td>
<td>Optimal number of UDAPs</td>
</tr>
<tr>
<td>(SM)</td>
<td>Smart meter</td>
</tr>
<tr>
<td>(N)</td>
<td>Number of SMs</td>
</tr>
<tr>
<td>(M)</td>
<td>Number of optimal UDAPs</td>
</tr>
<tr>
<td>(K)</td>
<td>Number of BSs</td>
</tr>
<tr>
<td>(\psi_i)</td>
<td>Number of hops</td>
</tr>
<tr>
<td>(S)</td>
<td>Set of candidate sites and SM latitude and longitude coordinates</td>
</tr>
<tr>
<td>(E)</td>
<td>Set of links</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Nomenclature</th>
<th>Algorithm</th>
</tr>
</thead>
<tbody>
<tr>
<td>(B)</td>
<td>Base station latitude and longitude coordinates</td>
</tr>
<tr>
<td>(d_{\text{max}})</td>
<td>Maximum distance of connection of the IoT technology</td>
</tr>
<tr>
<td>(\text{path})</td>
<td>Connection path for all devices</td>
</tr>
<tr>
<td>(T)</td>
<td>Optimal spanning tree georeferenced location</td>
</tr>
<tr>
<td>(G)</td>
<td>Connectivity matrix of SM–UDAP–BS</td>
</tr>
<tr>
<td>(\text{Cost})</td>
<td>Connection cost matrix</td>
</tr>
<tr>
<td>(D)</td>
<td>Distance matrix</td>
</tr>
<tr>
<td>(\text{links})</td>
<td>Connection links of SM–UDAP–BS</td>
</tr>
</tbody>
</table>

Algorithm 1 Main: Optimal Routing & Optimal \# \(Z_i\).

Input: \(S, B, \text{CapU}, d_{\text{max}}\)
Output: \(Z_i, \text{path}\)

Step 1:
\(T = \text{calc\_base\_tree}(S, \text{CapU}, d_{\text{max}})\)

Step 2:
\([\text{SolC, SolL}] = \text{greedyscp}(T)\)

Unique_UDAP = unique(SolC)

Step 3:
\([D, G, \text{Cost}] = \text{haversine\_matrix}(S, T, B, d_{\text{max}})\)

Step 4:
\(G = \text{sparse}(G)\)
\(\text{Cost}(isinf(Cost)) = 0\)
\(\text{Cost} = \text{sparse}(\text{Cost})\)

Step 5:
\([dp, pred] = \text{dijkstra}(\text{Cost}, N + M + K + 1)\)

Step 6:
for \(i = 1: N + M\)
node = \(i\)
\(\text{path(node)} = [\text{node}]\)
while \(\text{pred(node)} > 0 \& \text{pred(node)} < N + M + K + 1\)
\(\text{path}(i) = [\text{path}(i), \text{pred(node})]\)
\(T_{\text{Cost}} = T_{\text{Cost}} + D(\text{node, pred(node)})\)
node = pred(node)
endwhile
endfor

Step 7:
Return: \(Z_i, \text{path}\)
Algorithm 2 calc_base_tree (pre-selection of $Z_i$).

**Input:** $S$, CapU, dmax  

**Output:** $Z_i$

**Step 1:**  
Longitude = SM; $S$  
Latitude = SM; $S$  
index = 2 : length(Longitude)  
path = [0]

**Step 2:**  
while $Z_i < $ CapU & Hops $ < Hop_{max}$; flag=1  
while flag==1  
for $i = 1 : length(Z_i)$  
for $j = 1 : length(index)$  
dist = dist_haversine(SM, $S$)  
if dist $ > dmax$ path($i, j$) $ = \infty$  
endif  
endfor  
endfor  
if (dist is minimum)  
$T = [T, index(minimum dist)]$  
path = [path,path(minimum dist)+1]  
else  
break  
endif  
if length(SM>Cap)  
break  
endif  
endwhile

**Step 3:**  
Return: $T$

As a next step, an analysis of the cost and the existing links between the devices is carried out. Step 5 optimizes the links, taking into account the cost of connection, to find the optimal solution using Dijkstra’s algorithm. This is achieved through the function “haversine_matrix”, explained in Equation (5).

The result of Step 5 is the matrix of predecessors used in Step 6 to find the path that follows the information from each smart meter to the base station. This information is stored in the variable “path”, for further analysis. Consequently, the execution of Algorithm 1 is completed, and the graph of the deployment of concentrators with their respective connections to the SMs and BSs is presented.

The function “calc_base_tree”, outlined in Algorithm 2, has as inputs the coordinates of the smart meters, the coordinates of the UDAP candidate sites, the maximum capacity of the concentrators, and the connection range of the SMs. The first step of this algorithm is responsible for unifying the latitude and longitude coordinates of the SMs and UDAPs into a single vector and creating an identifier vector to differentiate the type of device (SM or UDAP).

In Step 2, the algorithm carries out nested iterations to select the appropriate locations of the UDAPs to meet the determined conditions of capacity, distance, and the number of hops. For this heuristic, if the distance between a UDAP and an SM or the distance between an SM and another SM is greater than the maximum distance established, it is considered to be not feasible, and therefore the distance is infinite.

On the other hand, in this loop, the analysis of the capacity for simultaneous connections of each UDAP is carried out without allowing the limit of allowed connections to be
reached. A final consideration for this heuristic is that if the number of hops present in a data path is higher than the established number, this connection will be discarded.

Hence, based on the restrictions analyzed in this algorithm, the pre-selection of the concentrators is completed. It is returned by the function in the “T” matrix.

Equation (5) outlines the function that “haversine” has in inputting the coordinates of the smart meters, the UDAP concentrators, and the base stations, as well as the maximum connection distance. This algorithm obtains the distance matrices $d_{ij}$ from the cost that refers to the matrix distance allowed by the wireless technology. Then, the matrix (G), which is the cost matrix (Cost), is formed.

\[
d_{ij} = \sin^2\left(\frac{\Delta \text{Lat}}{2}\right) + \ldots + \cos(\Delta \text{Lat}) + \cos(\Delta \text{Lat}) \sin^2\left(\frac{\Delta \text{Lon}}{2}\right)
\]

4. Analysis of Results

Once the simulation was executed with different radio coverages and different capacities for the concentrators, metrics were obtained that allowed the results obtained by the heuristics proposed in this document to be evidenced. Figure 3 shows the deployment and routing of the links, considering the scalability of the scenario.

This figure shows the geographical location of the smart meters and their optimal deployment by growth stages. Figure 3a shows the initial stage of the scenario where 89 smart meters are present, and the deployment is carried out for these users.

Subsequently, in Figure 3b, more users are integrated into the metering network, which then has 210 SMs. For this and subsequent cases, the locations of the candidate sites for the UDAPs were not changed, and the locations of the initial users were maintained.

Once the simulation of each stage was performed, it was observed that there are more active UDAPs in other stages than in stage 1. Additionally, some links switched to an optimal pathway under the proposed conditions. The changes in routing and numbers of UDAPs can be seen in the growth stages with 277 SMs in Figure 3c and 548 SMs in Figure 3d.

The algorithm adapts to the needs and optimizes the network according to the given connection constraints for all stages.

Figure 3 shows the different users (SMs), the points where the concentrators (UDAPs) have been deployed, and the locations of the base stations (BS), as well as the hops that the information makes before reaching its destination.

Figure 4 shows the variation in the number of hops present in the minimum spanning tree obtained as a function of the coverage radius of the simulated technologies; this information is additionally presented based on the capacity of the concentrators established for the analysis. The results shown in Figure 4 consider a connection range between 10 and 100 m, corresponding to the shortest range of ZigBee technologies in an urban area.

The metric shows that as the coverage radius increases within a range between 10 and 40 m, there is an increase in the number of hops necessary for the transmission of information. On the other hand, from 40 m onwards, the number of hops decreases, because greater connection distances can be spanned to reach hubs closer to the base stations, thus reducing the total number of hops in the route map.

On the other hand, Figure 5 shows the number of UDAPs deployed as a function of their connection capacity. The data are presented according to the stage of population growth being analyzed. The graph shows that, as the capacity of the concentrators increases, fewer UDAPs are needed to achieve network connectivity. The trend lines in the graph shown were obtained by simulating six different concentrator capacities, considering a maximum smart meter connection distance of 20 m. As previously, this metric considers the maximum connection distance of ZigBee technologies.
Figure 3. Optimal deployment of UDAPs obtained with the proposed heuristic. Radio coverage = 40 m, UDAP capacity = 5.
It is possible to determine each link path of the obtained spanning tree with the implemented heuristics. Table 4 shows the number of hops and the maximum distance of these hops resulting from the simulation, and also shows the average distance between the present hops in the path of the resulting aggregation tree. The data were obtained utilizing the path variable, which is part of the results produced by the algorithm developed in this study. The technology used for the analysis was Z-Wave, which connects at distances up
to 100 m. This technology was chosen because, in an urban scenario, it is one of the most restrictive in terms of distance to achieve a link.

Table 4. Maximum number of hops and resulting maximum distances, depending on the capacity of the UDAPs and the connection distance of the SMs.

<table>
<thead>
<tr>
<th>UDAPs Capacity</th>
<th>Wireless Ratio (m)</th>
<th>Max. Number of Hops</th>
<th>Maximum Path Distance (km)</th>
<th>Average Distance between Hops (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>80</td>
<td>8</td>
<td>1.3737</td>
<td>0.3070</td>
</tr>
<tr>
<td>10</td>
<td>20</td>
<td>11</td>
<td>1.8156</td>
<td>0.2941</td>
</tr>
<tr>
<td>15</td>
<td>30</td>
<td>12</td>
<td>2.9248</td>
<td>0.6639</td>
</tr>
<tr>
<td>15</td>
<td>50</td>
<td>7</td>
<td>1.7221</td>
<td>0.4532</td>
</tr>
<tr>
<td>20</td>
<td>40</td>
<td>8</td>
<td>1.7803</td>
<td>0.5763</td>
</tr>
<tr>
<td>20</td>
<td>60</td>
<td>6</td>
<td>1.2237</td>
<td>0.3933</td>
</tr>
<tr>
<td>25</td>
<td>70</td>
<td>6</td>
<td>0.9910</td>
<td>0.3435</td>
</tr>
<tr>
<td>25</td>
<td>10</td>
<td>5</td>
<td>0.4130</td>
<td>0.0205</td>
</tr>
<tr>
<td>30</td>
<td>10</td>
<td>5</td>
<td>0.4130</td>
<td>0.0188</td>
</tr>
<tr>
<td>30</td>
<td>20</td>
<td>15</td>
<td>3.0482</td>
<td>0.2887</td>
</tr>
</tbody>
</table>

Finally, the performance of the presented optimization method can be seen in Figure 6, which illustrates the elapsed processing time as the analyzed population grows. The processing time metrics were taken based on the heuristic stages. The metrics presented show the time taken to characterize the scenario through the .osm file, i.e., the time taken to pre-select the UDAPs, calculate the cost and distance matrices, and identify the optimal path used.

The simulation results show that the proposed architecture and link routing minimizes the use of resources in IoT-based technologies. The implemented heuristics allow experimentation with technologies such as ZigBee, which has connection distances from 10 m to 75 m, and technologies that work with distances greater than 100 m. Additionally, the deployment optimization presented in this document is flexible and adaptable to any wireless technology, as long as it is characterized in the simulation scenario studied based on the restrictions contemplated in the heuristics.

5. Conclusions

The use of wireless communication technologies considering optimal deployment and reduced cost is necessary to achieve an efficient, reliable, and resilient advanced metering infrastructure that integrates with the requirements of a smart grid.

This paper presented a model for the effective deployment of a wireless communication network that can be evaluated in urban, suburban, and rural scenarios, considering the scalability of the number of smart meters deployed.
The deployed communication network is intended to guarantee the total coverage of smart meters, and the collection of information is consistent with the demand response. This management process requires updated information, to reduce errors in predicting the electric power load curve.

The proposed heuristic model minimizes the use of resources (UDAPs) and determines the optimal link path between smart meters and universal data aggregation points. The NP-complete-type problem evaluated in this work justifies a heuristic technique based on graph theory and uses georeferenced information to add value to previous publications.

The heuristic model considers connection capacity restrictions for the universal data aggregation points based on an optimal spanning tree. The coverage distance of the smart meters is determined by the type of wireless technology and the possibility of restricting the number of hops in the link routes at the same time, to optimize resources and reduce the likelihood of the latency that can be generated by having indiscriminate hops.

The results show in their objective functions the determination of path minimization and the minimum number of UDAPs. Consequently, the results show how the model behaves in the face of a gradual increase in smart meters. This simulated effect is characteristic of an in-situ deployment, as smart meters are gradually incorporated into the power grid in its expansion process.

The model also helps to identify smart meters that may have been left out of the coverage, thus aiding in proposing a different wireless technology for only one sector of the area under study. The model’s results show the path for transmitting the electric metering information from the supply to the central office of an electric distribution company.

The heuristic model developed can simulate the behavior of the network under the parameters of new technologies that may be made available in the future. For this purpose, it is necessary to utilize the coverage distance of such a technology and the number of hops it can support without latency. In addition, it is noted that the model, when considering the capacity of the UDAPs, accounts better for an actual situation, compared to commercial equipment, in terms of the number of simulated connections it can handle.

In this paper, the analysis was performed for the shortest range technologies, between 10 and 100 m. These are the most difficult to connect in an urban scenario. However, the algorithm can be applied to all the technologies discussed in the Introduction section of this paper, provided the simulation parameters are set according to the parameters of each IoT communication technology.

Author Contributions: L.M.: conceptualization, methodology, validation, and writing—review and editing. L.M.: conceptualization, methodology, software, and writing—original draft. L.M.: data curation and formal analysis. E.I.: supervision. E.I.: writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This work was funded by the Smart Grid Research Group (GIPE) of Universidad Politécnica Salesiana (Project: Charging of electric vehicles in buildings and its impact on the sizing and planning of electrical distribution networks) and by Power Grids and Smart Cities (RECI-IUS).

Acknowledgments: This work was supported by Universidad Politécnica Salesiana and GIPE—Smart Grid Research Group under the project “Electric vehicle charging in buildings and its impact on the sizing and planning of electricity distribution networks”.

Conflicts of Interest: The authors declare no conflict of interest.
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