Accelerated Network Design for Analyzing Spatial Heterogeneity in Electrification Planning

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***Abstract*—Electricity access in rural sub-Saharan Africa remains a significant challenge. Settlement patterns in this region exhibit considerable heterogeneity, significantly impacting distribution network layouts and investment costs. This paper analyzes settlement patterns within communities using a network design model that minimizes transformer count and aggregate costs of LV and intra-community MV infrastructure. The optimization results provide key network metrics for each community, including transformer counts, low-voltage wire, and internal medium-voltage wire requirements per connection. This model builds upon an established two-level network design algorithm while incorporating significant computational improvements. Tests show a two orders of magnitude reduction in computational time by relaxing the voltage drop constraint while maintaining exceptional fidelity in distribution infrastructure cost per connection. Meanwhile, the maximum input size of connection nodes that can be computed is nearly three to four times larger, reducing boundary effects. Additionally, a geospatial outlier exclusion methodology prevents community cost metrics from being distorted by spatially distant connection nodes. These improvements enable the algorithm to be applied to large-scale networks with less time, reduced segmentation requirements, and smaller effects of geospatial outliers. These enhancements allow planners to identify prioritized electrification communities and allocate resources strategically across diverse settlement patterns.**

***Index Terms*—sub-Saharan Africa, electricity access, distribution network, computational efficiency, spatial heterogeneity**

I. Introduction

An estimated 600 million people in sub-Saharan Africa lack access to electricity [1], with this deficit most severe in rural areas [2]. The absence of electricity infrastructure across vast rural regions hampers local economic development, as power access is essential for productive activities and improved living standards [3]. With limited financial resources to address this widespread challenge, electrification efforts require careful assessment and strategic planning to design sustainable pathways that maximize the impact.

Rural communities without electricity access generally have three options: grid extension, mini-grid systems, or solar home systems [4]. When end-users require more electricity than individual solar home systems can deliver, grid extensions and mini-grids become viable options, both requiring properly designed distribution networks to connect customers. These networks represent critical infrastructure components and significant cost factors in electrification projects [5]. Distribution networks can be optimally designed using computational models when building footprints and topography are known. These models provide valuable insights into equipment requirements and cost estimations, enabling more efficient resource allocation [6]. This study contributes to this vital aspect by presenting an improved approach for planning electricity distribution networks in unelectrified areas, supporting electrification across diverse sub-Saharan African contexts.

Rural electricity distribution network design is a challenging optimization task, and researchers have developed different algorithms to minimize the total infrastructure costs. Early work modeled network design as single-level minimum spanning tree (MST) problems, connecting all consumers by low-voltage (LV) with minimum total line length [7]. However, when the network spans several kilometers, medium-voltage (MV) feeders become necessary to link multiple LV sub-networks through transformers.

A review study [6] shows that most multilevel network design models share the goal of cost minimization and fall into two categories: heuristic/metaheuristic approaches and mixed-integer linear programming (MILP) approaches. For example, Costa et al. [8] proposed an early two-level design approach that first determines transformer locations using a k-median problem and then uses mixed-integer programming that optimizes both MV and LV levels. Kocaman et al. [9] developed a two-level network design algorithm that uses agglomerative clustering to place transformers and a heuristic algorithm to design the LV networks. Both algorithms decompose the problem into transformer placement and local network design to reduce computational complexity.

Fobi et al. [10] developed the two-level network design (TLND) algorithm for scalable, national-scale network planning, integrating previous work [9]. The approach uses spatial decomposition to divide large regions into manageable cells, with each cell optimizing transformer placement and MV/LV network layouts. However, when applying this approach in other regions, several key areas for improvement were identified.

- Computational time: The model's slow computation limits its practical implementation. For example, processing a community with over 500 nodes may require more than an hour. The node refers to the connection node in the network design model. Therefore, a nationwide simulation would need enormous computational resources.
- Maximum input node limits: Due to computational constraints, the model is suggested to be applied with up to 1,000 nodes. Large communities must be split into smaller cells, creating inefficiencies at boundaries where nodes that could share transformers are separated across computational divisions.
- Outlier-induced high costs: The model connects all input nodes. However, some spatially outlying demand nodes often require dedicated transformers and long electric lines, disproportionately increasing the average per-node cost estimates. It will potentially disqualify otherwise viable communities from electrification programs.

This paper introduces the accelerated two-level network design (Accel-TLND) algorithm to address the identified limitations. The algorithm achieves substantial computational speedup while maintaining high result fidelity by relaxing the voltage drop constraint. Additionally, it incorporates a geospatial outlier exclusion methodology that prevents community cost metrics from being distorted by spatially distant nodes. These enhancements enable efficient large-scale implementation for analyzing settlement spatial heterogeneity and its impact on distribution infrastructure investments.

In this paper, the analyzed communities are specifically targeted locations, each defined within a 1-km radius circle as detailed in the methodology section. For each community, the LV and internal MV networks with transformer locations are designed to connect all demand nodes. These communities serve as inputs for comparing the original and accelerated algorithms and demonstrating the model's capabilities and practical applications. However, the algorithm can be applied more broadly for general purposes, such as designing networks for an entire nation with careful subdivisions.

II. Distribution cost per node: quantifying settlement heterogeneity

Settlement spatial patterns significantly influence rural electricity infrastructure costs, with nucleated settlements requiring shorter lines and fewer transformers than dispersed communities. This distinction exists even between communities with similar node counts and population densities. Fig. 1 compares two heterogeneous spatial patterns with similar node counts: a dispersed settlement (371 nodes) versus a nucleated settlement (377 nodes). The nucleated community reduces per-node distribution costs to just 39% of the dispersed community. Due to household proximity, nucleated settlements require fewer transformers and significantly reduce the length of MV and LV lines. The network design illustrated here demonstrates the settlement's spatial heterogeneity. Further details about the modeling are presented in the methodology and results sections.

When applied at a large scale to thousands of communities, the distribution cost per node metric derived from these calculations captures critical settlement heterogeneity patterns. This insight motivated our work to accelerate the network design model for large-scale analyses that can effectively guide electrification planning and investment prioritization.

III. Methodology of Accel-TLND

The original TLND [10] consists of three key steps: (1) Node clustering and transformer placement, (2) LV system design under each transformer, and (3) MV design connecting transformers. The newly developed model maintains these three steps while dramatically enhancing computational efficiency, hence the name Accel-TLND, with the original algorithm referred to simply as TLND. All potential electricity service points are referred to as nodes throughout this paper. The code is available in an open-source GitHub repository[1]. This section examines each step and details the specific improvements implemented in Accel-TLND.

First, TLND uses an agglomerative hierarchical clustering approach for node clustering and transformer placement. The process begins by assigning each node as a transformer, creating individual clusters. The algorithm then iteratively evaluates potential cluster pairs, calculating centroid distances between all pairs and attempting merges from the closest pairs outward. For each potential merge, it calculates the combined cluster's centroid and verifies all demand nodes remain within a specified maximum Euclidean distance (e.g., 500 meters in this paper) from this new centroid. When these conditions are met, the clusters are merged and the transformer is repositioned at the new centroid. This continues until no further feasible merges are possible, efficiently minimizing transformer count while ensuring each transformer serves nearby demand nodes within distance constraints.

When the input contains n nodes, this algorithm evaluates $O(n^2)$ potential cluster pair merges. For each potential merger, the algorithm must verify distances for $O(n)$ nodes, resulting in an overall computational complexity of $O(n^3)$. Computation time increases with node count but follows predictable scaling, enabling reliable estimation. We retained this clustering algorithm because it preserves the high-quality results and network framework consistency of the original TLND. In implementation, the algorithm was re-coded but preserving its core mathematical approach.

The original TLND step (2) designs LV networks for each node cluster using the Capacitated Minimum Spanning Tree (CMST) algorithm with Esau-Williams heuristic [11]. A key constraint is the maximum LV path length from the transformer to the nodes, which controls voltage drop and maintains electricity quality. This step minimizes total wiring

[1]The model is available at: https://github.com/SEL-Columbia/accel_tlnd

Community	Nodes	LV per node	MV per node	Transformers	Costs per node
Example in Mitooma	371	56.9 m	12.9 m	10	$781
Example in Kotido	377	19.2 m	6.3 m	4	$306

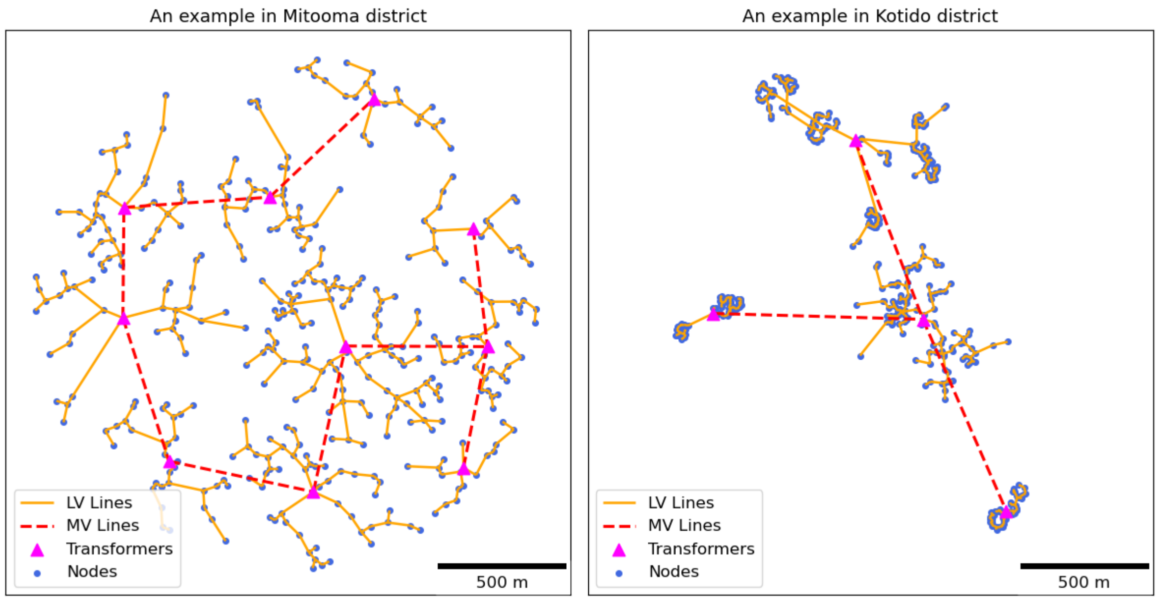


Fig. 1. Two illustrative examples of communities with similar node numbers but different settlement patterns at the same geographic scale. The left panel shows a dispersed settlement pattern, while the right panel displays a nucleated settlement pattern.

length while ensuring that no transformer-to-node accumulated path length exceeds the defined limit.

This LV design process is computationally intensive, with execution times varying significantly based on network topology. Compared to step (1), this process consumes substantially more computation time, making it the primary optimization target. A key finding was that replacing CMST with a simple MST algorithm dramatically reduces solution time to seconds. Comparative experiments revealed that MST results differ minimally from CMST results, which is logical since the cluster boundaries determined in step (1) already limit potential network configurations. For large-scale estimations, this computational advantage justifies relaxing the voltage drop constraint. In practice, MST is implemented in the Accel-TLND using Kruskal's algorithm.

After a large-scale network evaluation, communities of greater interest can implement solutions with preserved voltage drop constraints. For this purpose, an optional MILP configuration is developed that optimizes network designs while maintaining the voltage drop constraints. The mathematical formulation is provided in the GitHub repository. However, this configuration is not the focus of this paper; we mention it only as an available option. Throughout this paper, Accel-TLND refers to using the MST method for LV network design.

The original TLND step (3) for MV system design employs a straightforward MST approach. The Accel-TLND keeps it and implements Kruskal's algorithm-based MST, which is consistent with the approach used in the LV design. This component consumes minimal computational resources compared to other steps.

In this paper, another significant improvement is the outlier exclusion. It addresses the significant distortion that a few geospatial outliers can create in community distribution cost metrics. An automatic process is needed to handle outliers for large-scale applications. We integrated the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm for this purpose. DBSCAN iteratively expands clusters by connecting nodes within a specified distance threshold, grouping nodes in dense regions while classifying sparse nodes as outliers. DBSCAN was selected because it naturally identifies outlier nodes and accommodates non-spherical clusters common in real-world settlements that follow roads or terrain features. The algorithm requires two parameters: a distance threshold defining node proximity and a minimum node number needed to form a cluster, set at 100 meters and five nodes in this study, respectively. When the outlier exclusion function is selected, it is applied as a pre-processing step before input into the network design model.

To demonstrate the network design methodology, we define communities for algorithm application. These targeted communities are based on the presence of at least one petroluse or manual-driven productive use of electricity (PUE) customer, identified from survey data [12]. These PUE activities include grinding mills, refrigeration, welding, and other business activities. PUE customers typically ensure substantial electricity consumption and the ability to pay [13]. Therefore, communities with PUE activities have demonstrated higher success rates for rural electrification projects [5]. This paper uses these PUE-anchored communities as candidates for distribution network design analysis.

Using the PUE location (or geometric center when multiple PUEs exist) as the community center, we draw a 1-km radius circle that defines the community boundary. Within these circles, household locations are identified for network design. These household locations are derived from Google's Open Buildings dataset [14] and processed to align with Uganda census data [15], with details available in the GitHub repository. Both PUE customers and household customers are collectively defined as connection nodes for network design purposes.

This paper analyzes 7,018 potential electrification communities across Uganda for network design, retaining only communities with at least 20 nodes, with the largest containing 3,797 nodes. Given the community size with a 1-km radius, while the maximum Euclidean distance of 500m from a transformer to its connected node, the communities require both MV and LV networks. Network design algorithms are applied to determine optimal transformer locations and electric wire routing within each community. From the resulting infrastructure layouts, we calculate the community's distribution costs per node. Cost calculations use the following assumptions: \$8 per meter for LV wire, \$20 per meter for MV wire, and \$2,500 per distribution transformer.

IV. Computation Performance Evaluation

This section examines the computational performance differences between TLND and Accel-TLND when applied to the targeted communities for network design. Due to TLND's maximum input size and computational time constraints, this evaluation was limited to communities with up to 884 nodes. From this eligible pool, 20% (1,324 communities) were randomly selected for computational performance testing, providing a representative sample for comparing both algorithms. Both TLND and Accel-TLND processed this subset for computation time evaluation. TLND required CPU 423.4 core-hours to finish, while Accel-TLND required only CPU 3.2 core-hours, which is a 132-fold improvement. This efficiency gain would be even more pronounced for larger networks with more than 884 nodes. All computations were performed on an Apple M1 Pro chip using eight cores in parallel. This parallel processing reduced the actual wall-clock time by approximately eight. However, results are reported in single-core computation time for consistency.

Fig. 2 illustrates computation times of each test community. Due to TLND's wide computation time range, the plot uses two panels with different y-axis scales sharing the same x-axis. The main panel uses seconds as the unit, while the top panel uses minutes for more straightforward interpretation. The main panel shows computation times for both algorithms on the same 1,324 communities. For comparison, the right panel displays Accel-TLND's performance on additional larger networks with up to 2,041 nodes, with computation times remaining under 2000 seconds. Additionally, the largest tested community contains 3,797 nodes and completes in 171 minutes, which is comparable to some TLND cases with only 500 nodes. This finding highlights the significant computational efficiency gains achieved by Accel-TLND.

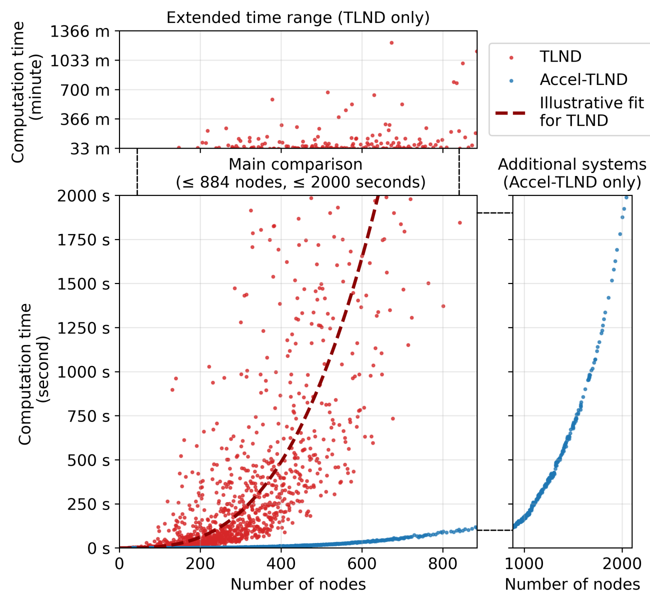


Fig. 2. Computation time against number of nodes in the network, comparing TLND and Accel-TLND algorithms.

Fig. 2 shows that the computation time grows exponentially with input nodes for both algorithms, with TLND's fitting line increasing far more steeply than Accel-TLND's. A notable difference is TLND's large computation time variations versus Accel-TLND's minimal variation. As discussed in the methodology section, node clustering and transformer placement result in $O(n^3)$ computational complexity with input node number n, and the MST algorithm requires minimal processing time. The results confirm that computation time scales approximately as n^3 with node input in Accel-TLND, with overall computation primarily determined by the clustering step. In contrast, TLND utilizes a heuristic algorithm for local LV network design with no guaranteed computation time bounds, causing the significant variations in processing time observed in Fig. 2.

Meanwhile, the Accel-TLND produces results remarkably similar to the original TLND model. For the distribution cost per node metric comparison between the two algorithms, the correlation coefficient is 0.999. The mean metric difference across communities is only 3.56%, where only 0.6% of the communities exhibit differences greater than 10%. This similarity stems from the node clustering and transformer placement steps performing identically with both models. Once the clustering is complete, the network framework is largely established, with variations arising only from local LV layout differences.

In more detail, the original TLND creates more branches to satisfy voltage drop constraints with maximum transformer-to-node distances, while Accel-TLND forms longer, continuous lines using minimal total wire length. Generally, Accel-TLND produces slightly lower cost estimates by relaxing maximum LV wire distance constraints. These minimal differences indicate that Accel-TLND produces sufficiently accurate distribution cost per node results for practical applications.

This section demonstrates that Accel-TLND is an excellent alternative to the original algorithm. For large batch processing, Accel-TLND achieves significant computational speed improvements while producing results with negligible differences when evaluating community settlement spatial heterogeneity.

V. Outlier Exclusion

Building on the DBSCAN outlier exclusion methodology, this section analyzes the impact of outlier exclusion on community distribution network design economics using Accel-TLND. This approach addresses the typical rural pattern of isolated nodes that could disproportionately increase distribution costs.

Fig. 3 shows the impact of outlier exclusion for the illustrative community in Butaleja district. The algorithm identified and excluded 19 nodes (4.6%) from 414 total nodes, marked as black squares in the figure. This exclusion reduced distribution costs from \$571.9 to \$460.0 per node (19.6% decrease). For example, in this figure, the top-left area shows two distant nodes marked as black squares that are excluded by the outlier exclusion algorithm. Without outlier exclusion, these two nodes would require a dedicated transformer and additional MV lines to connect them to the network. With outlier exclusion, these nodes are removed from the design, eliminating substantial investments in transformers and MV infrastructure. Similar cases can be observed throughout this figure, and this example represents a common scenario in rural electrification design across many communities.

If in a national-scale planning scenario using a \$500/node threshold for prioritizing electrification investments, the community shown in Fig. 3 would be ineligible without outlier exclusion. But it becomes viable after removing 19 geospatially distant nodes. This approach effectively identifies communities where costs are disproportionately inflated by a few distant nodes, thereby enhancing the selection process for prioritizing optimal electrification areas.

Next, outlier exclusion was applied to all 7,018 communities as defined in the methodology section. Significant changes were observed across communities. Fig. 4 illustrates the percentage change in distribution cost per node following outlier exclusion implementation. Results reveal that 89% of the communities experienced cost reductions, with 2,397 communities (34% of the total) showing decreases greater than 10%. This demonstrates the substantial effectiveness of outlier exclusion in optimizing distribution network costs across a significant portion of potential electrification communities.

A small subset of cases exhibits a 100% reduction, representing extreme scenarios where communities with minimal distant nodes were entirely filtered out, resulting in no network implementation. These results suggest network deployment would be economically unfeasible in such locations.

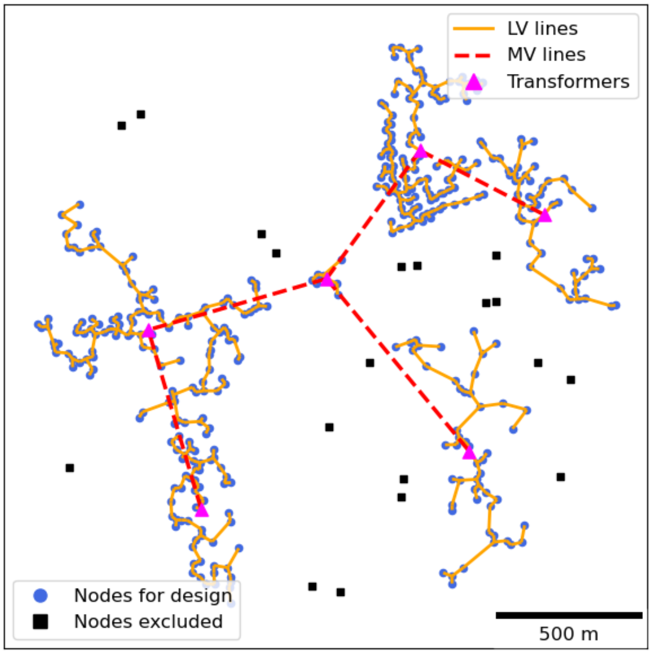
However, 11% communities experienced counterintuitive cost increases after outlier exclusion, with approximately 112 communities (1.6%) showing increases greater than 10%. Further analysis revealed that these communities share common characteristics: low-density nodes widely dispersed throughout the region. In such cases, the exclusion algorithm identifies many nodes as outliers, leaving behind smaller, more fragmented networks where costs (such as transformers) are distributed across fewer remaining nodes, thus increasing the per-node cost. Despite this phenomenon, these communities generally exhibit high distribution cost per node metrics both before and after outlier exclusion, making them unlikely candidates for prioritized electrification investment regardless of the exclusion process.

Using a threshold of \$500 distribution costs per node to identify priority communities for electrification investment, we found that 1,528 communities qualified under the standard design approach that included all nodes. When applying our outlier exclusion methodology, this number increased to 2,073 communities. This approach prevents overlooking potentially viable electrification communities. To maximize qualifying communities, a hybrid approach is used that selects the lower-cost solution between the two methods. This strategy identifies eight additional qualifying communities below the \$500 per node threshold.

The spatial outlier exclusion approach does not imply that excluded households should remain without electricity access. Alternative solutions such as solar home systems could serve these outlying nodes, or networks might expand to include them as communities develop. This outlier exclusion method in this paper provides an option for electrification planning, facilitating efficient allocation of limited resources to maximize impact during initial deployment phases.

VI. Application of the Model and Discussions

This section demonstrates Accel-TLND's capability to enable stakeholders to identify promising electrification communities. The analysis examines network designs for 7,018 targeted communities as a case study. As defined in the methodology section, communities are those within a 1-km radius containing both PUEs and households. Accel-TLND was applied to each community to design the internal LV and MV infrastructure requirements. Each community



Scenario	Design with all nodes	Design with outlier exclusion
Nodes for design	414	395
Nodes excluded	0	19
LV length (m) per node	37.6 m	33.5 m
MV length (m) per node	10.8 m	7.7 m
Number of transformers	9	6
Costs ($) per node	$572	$460

Fig. 3. Impact of geospatial outlier exclusion on network design and cost metrics, for an example location in Butaleja, Uganda.

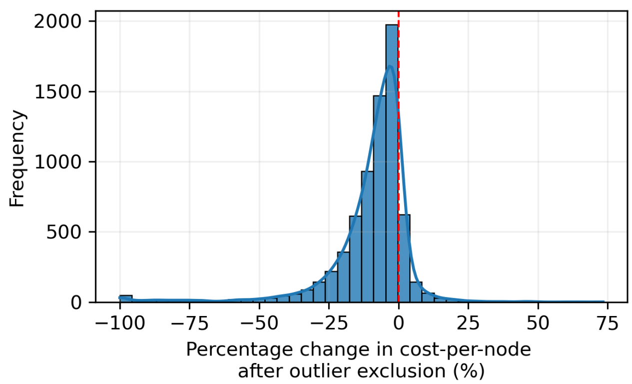


Fig. 4. Distribution of percentage changes in cost per node after outlier exclusion.

was modeled both with and without the outlier exclusion methodology, with the version producing lower distribution cost per node selected for analysis.

Fig. 5 displays these communities as points on the map, illustrating two key features: node numbers and distribution cost per node in USD. Node numbers are represented by point size, while the distribution cost per node is indicated by color. Combining both metrics, communities shown in lighter yellow or green colors (low per-capita investment costs) and the two largest size tiers (high node numbers) represent priority candidates for electrification planning.

The distribution cost per node provides the spatial heterogeneity, and the node count provides the economic size. Both metrics for each community can inform mini-grid development or grid extension decisions, depending on proximity to the national grid infrastructure. Since the analyzed communities integrate unelectrified PUEs, those with favorable distribution costs present viable candidates for prioritized electrification.

This map shows that some districts contain more communities with lower per-node costs, while others consist primarily of high per-node cost ones. This suggests that electrification planning could be strategically applied to certain districts first, particularly where districts have more nucleated settlement patterns and larger community sizes around PUEs. Note that areas with few communities are caused by a lack of unelectrified PUEs, some of them potentially indicating existing electricity infrastructure.

The Accel-TLND is applied to pre-defined communities with PUEs, which are specifically for model comparisons and demonstrating the case study in this paper. However, this algorithm can be applied more broadly for general purposes, such as designing networks for large regions with continuous geospatial areas. This approach may involve careful subdivisions that allow the model to design one large chunk at a time, and aggregate them after each is completed. Therefore, it enables comprehensive planning across extensive territories such as a nation.

In the outlier exclusion scenario, electrification plans for distant demand nodes are not included in the current analysis. In more comprehensive future studies, generation should be considered together with distribution infrastructure evaluation, so that grid extension, mini-grids, and solar home systems

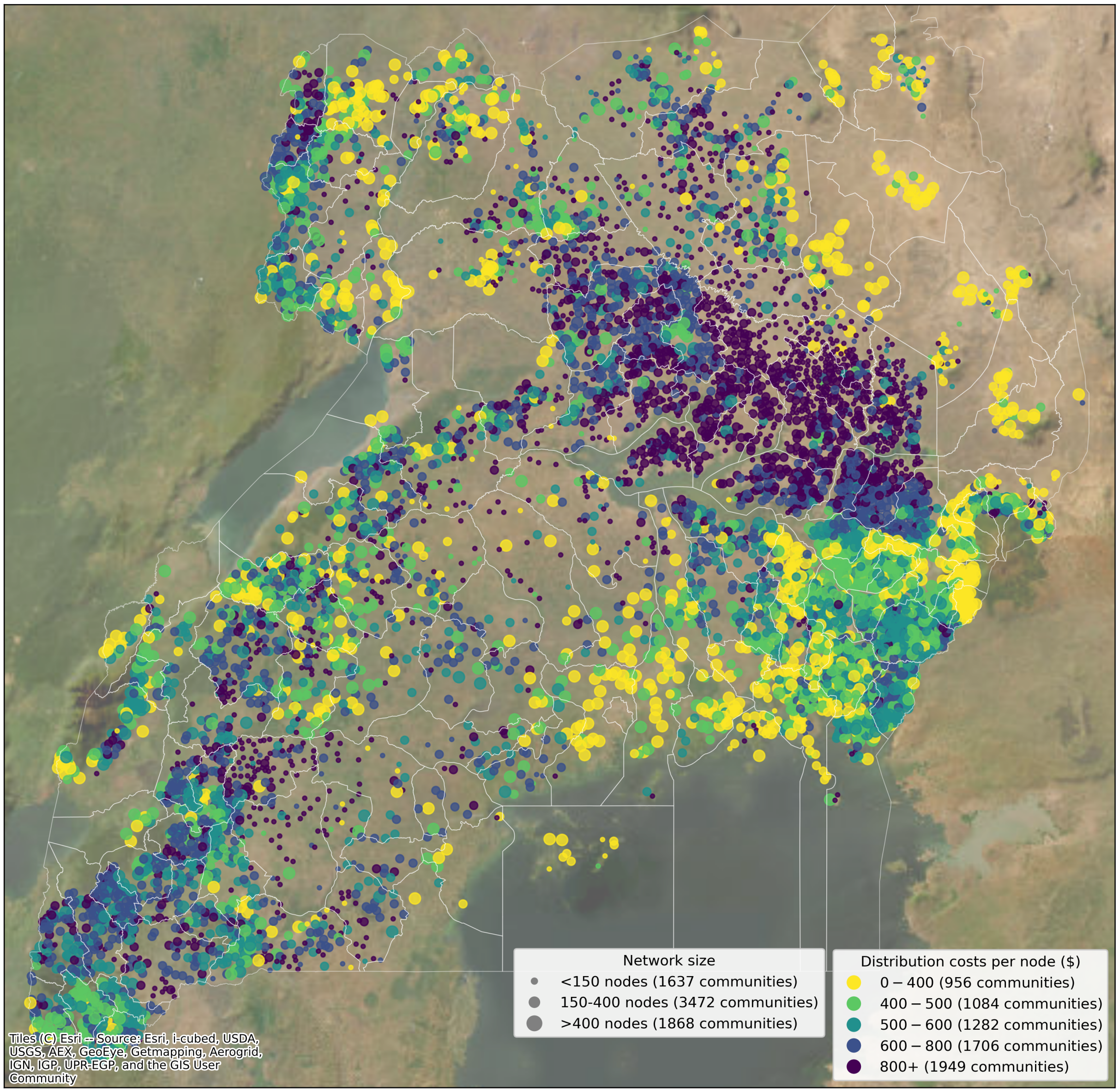


Fig. 5. Distribution network design results for 7,018 PUE-anchored communities in Uganda (cost assumptions: $8 per meter LV wire, $20 per meter MV wire, $2,500 per transformer).

could be evaluated together. This paper focuses on distribution infrastructure assessment and can provide the foundation for such integrated studies. Additionally, future research could investigate how settlement heterogeneity affects local economic development levels and actual infrastructure conditions.

While Accel-TLND provides valuable planning insights, several limitations should be noted. The Accel-TLND algorithm connects all nodes remaining after outlier exclusion. In practical scenarios, some nodes may remain unconnected even when grid extension is available, due to various implementation constraints. Consequently, actual costs may vary from these estimates. This model does not claim to calculate precise costs, but instead estimates settlement spatial heterogeneity, indicating where infrastructure development would be more economical for electrifying equivalent households. Additionally, the current implementation does not consider geographic parameters such as rivers, hills, and other topographical features. Despite these limitations, the model serves as a valuable tool for national-scale examination and provides meaningful insights for electrification planning.

VII. Conclusion

This study presents advancements in a two-level electricity distribution network design methodology named Accel-

TLND that addresses limitations in the previous approach. These improvements were motivated by computational barriers encountered when applying the original TLND to larger regions. There are three major improvements. (1) The new method achieves substantial computational efficiency while maintaining exceptional similarity in distribution cost per node results compared to the original TLND. (2) The methodology effectively handles larger networks without subdivision, eliminating boundary inaccuracies. (3) The geospatial outlier exclusion methodology prevents distribution cost per node metrics from being skewed by distant nodes.

The case study analyzed targeted communities within a 1-km radius, designing LV and internal MV networks for each. It demonstrates the practical utility of Accel-TLND. The results effectively identify high-priority communities with sufficient customer numbers and lower per-node distribution costs. This provides valuable insights for both public planners and private investors in electrification planning.

The combined improvements advance the state of practice in rural electricity distribution two-level network planning. They enable rapid and accurate network design at national scales. By providing a robust distribution cost per node metric that quantifies settlement spatial heterogeneity, this methodology equips decision-makers with tools to allocate limited resources for maximum impact strategically.

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