Sensitivity Analyses of Synthetic Power Grid Modeling Techniques in a Global Context: A Case Study in Ghana

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Abstract

Synthetic power grid models play a pivotal role in algorithmic benchmarking and techno-economic policy analysis. Existing synthetic grid research has primarily focused on regions in the United States and Europe using methods based on these regions' characteristics. This paper examines these methods' suitability for creating representative models for other regions. Differing data availability, power consumption behaviors, and applicability of various modeling assumptions challenge the suitability of existing synthetic grid methods for non-Western countries. Our analysis focuses on the West African country of Ghana. We evaluate methods for estimating electric demand and transmission network topologies by benchmarking them against a representation of Ghana developed in our previous work that is based on an accurate network topology and public reports. Our results indicate that existing population-based demand assumptions may be inapplicable. Transmission topology methods can yield reasonable results when aggregate characteristics match those of the real system, but they do not capture the centralization of Ghana's grid.

Keywords: Synthetic grids, Delaunay triangulation, minimum spanning tree, per capita power consumption.

1. Introduction

By allowing researchers to benchmark algorithmic innovations and perform techno-economic policy analyses using realistic power grid models that only rely on publicly available information, synthetic grid development is a crucial enabler of power systems research [1]–[4]. Synthetic grids provide realistic test cases for testing new algorithms and are also useful for educational and training purposes [5]. Synthetic test cases are especially valuable for addressing problems that are strongly influenced by regional characteristics, e.g., wildfire risk mitigation, expansion planning, etc.

Nearly all synthetic grid research has focused on the United States and Europe, e.g. [6]–[9], with few synthetic grids available for other parts of the world. To our knowledge, the few exceptions include regions of South Korea [10], Singapore [11], and Saudi Arabia [12]. There is a notable absence of synthetic grids for developing countries in Africa, Asia, and South America. With researchers implicitly tailoring their analyses to the characteristics of the available synthetic grids, this lack of test cases for developing countries may limit the geographic applicability of emerging algorithms as well as the accuracy of techno-economic policy assessments in an international context.

Beyond the models themselves, most methods for creating synthetic power grids (e.g., Delaunay Triangulation and population-based demand estimates) and validation metrics (e.g., average nodal degree) have been developed based on grids in the United States and Europe, e.g., [1], [2], [13]. It is unclear whether these methods can be directly applied to African, Asian, and South American countries, especially those with significantly different characteristics in terms of population distribution, economic development, electricity access, and urbanization rates.

Building on our prior work in [14], this paper investigates the applicability of existing synthetic grid creation methods for countries in Africa, using Ghana as a case study. In [14], we combined public information on the actual transmission topology with field reports, utility company statements, and online databases from economic development organizations to create a detailed synthetic model that accurately represents the demand, generation, and transmission network characteristics of Ghana's power system. The approach described

*This work was performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under Contract DE-AC52-07NA27344 and was supported by the LLNL LDRD Program under Project 25-SI-007.

in [14] required extensive manual effort and the public availability of various datasets. Repeating this approach to create realistic synthetic models for many developing countries would thus be challenging, motivating the application of existing methods that automate the creation of synthetic grids. However, it is not clear whether existing methods produce reasonably accurate synthetic models for non-Western countries.

Ghana's grid, in particular, is highly centralized, relying heavily on a small number of generators–notably the Akosombo Dam–and key transmission nodes such as the Kumasi substation [14]. This contrasts with typical characteristics of other power systems studied in [15], particularly that typical systems lack central hubs with a high degree and instead follow an exponential nodal degree distribution. As modeled in [14], Ghana's network exhibits a few outlier buses with disproportionately high degree, and such structural differences could have significant implications for overall network topology and behavior. These and other distinctive characteristics raise concerns regarding the applicability of existing synthetic grid creation methods.

To help address this question, we assess the validity of applying existing synthetic grid methods to Ghana's power system. We specifically compare our most accurate model from [14] with alternatives that estimate the demands and transmission network topology using population-based methods and Delaunay triangulation techniques, as in prior literature. Our results show that population-based demand estimates can work well in aggregate but may fail to produce accurate spatial distributions. Conversely, prior transmission topology techniques can provide realistic results, especially when the average nodal degree is known. In summary, this paper makes the following primary contributions:

- By applying existing grid estimation methods, we identify data shortcomings that limit the direct application of these methods in the Ghanaian power system context and modify how they are applied to make these methods more suitable.

- We compare models developed with existing estimation methods to the realistic model created in [14] that uses actual data for the network topology and other power grid characteristics. These comparisons assess differences in demand distribution, Delaunay separation of lines, and DC optimal power flow (OPF) solutions.

The remainder of the paper is organized as follows. Section 2 describes the Ghana grid from our prior work [14]. Section 3 discusses synthetic grid estimation methods and explains our implementations. Section 4 presents and analyzes our results for the comparison. Section 5 concludes the paper and discusses future work.

2. Modeling the Ghana Grid

Using publicly available data, our previous work in [14] developed a realistic synthetic model of Ghana's electric grid in the MATPOWER [16] format.[1] This section describes our Ghanaian grid model and summarizes our development approach; see [14] for further details. Note that creating this model required significant manual effort to combine and cross-check various data sources, and prior knowledge regarding the local context was employed. This is a key motivation for investigating the use of automated estimation techniques to develop realistic synthetic networks, especially for cases like Ghana that lack centralized, complete data sources for the overall power system.

2.1. Generation

Ghana's power system includes hydropower, natural gas, and solar generators. We modeled these generators using data on capacities and operating costs from multiple sources, including the Ghana Grid Company's 2022 Annual Report [17] and a Japan International Cooperation Agency report [18]. To estimate the generators' reactive limits, we used the method from [1].

2.2. Demand

The Ghana Energy Commission provides data on the power consumption in all Ghanaian districts [19]. Using this data and the total national electricity consumption from the Ghana Grid Company [17], we computed the average consumption for each district in Ghana. To determine the substations' power demands, we spatially assigned each district to the closest substation. The power factor for the demand is set to 0.95, consistent with the Ghanaian Renewable Energy Grid Code [20].

2.3. Transmission

Detailed data on the network topology and electrical parameters, including nominal voltage, resistance, reactance, and flow limits, are needed to create a realistic representation of the Ghanaian transmission network. The Economic Community of West African States (ECOWAS) Center for Renewable Energy and Energy Efficiency (ECREEE) provides a database of transmission lines in the West African region [21]. This ECOWAS database formed the basis of our transmission network model, providing information on the length of each line, its connected substations, and the voltage level at which it operates. Our original model [14] represents each substation as a single bus to create the initial

[1] The model data is available at https://doi.org/10.5281/zenodo.15557023.

topological skeleton upon which the rest of the network is built. We extended this model to incorporate multiple buses with transformer connections in substations that connect different nominal voltages.

Several sources were used to determine the electrical parameters. First, field reports from the Japan International Cooperation Agency and the World Bank provided parameter values for all transmission lines in the Greater Accra region [18], [22]–[25]. For lines that do not appear in any field reports, and thus lack detailed parameter data, we estimated resistances, reactances, susceptances, and flow limits using line length and voltage level data obtained from ECOWAS, following techniques similar to those in [1].[2] This provided a realistic representation of the Ghanaian transmission grid network, as shown in Fig. 3a.

3. Automated Estimation Methods

Creating the Ghanaian power system model described in Section 2 involved extensive manual effort and relied on the public availability of various data. Repeating this approach for other developing countries is thus challenging and may not be possible, depending on data availability. Thus, using automated synthetic grid creation techniques from prior literature would be particularly valuable in the context of non-Western countries. To assess whether prior synthetic grid modeling techniques yield acceptable results, this section describes these prior techniques in the context of Ghana to develop alternative models that we will subsequently numerically compare in Section 4.

Note that we assume the locations of all substations and generators are known, as this information can be found using publicly available satellite imagery [26]. Demand information is not extractable from such software, and transmission line topology, where available, is not as reliable or easy to obtain [27].

3.1. Estimation of electricity demand

Population is often a good indicator of power consumption. Previous studies use the population data for various regions and the respective power consumption per capita to estimate load demands at all substations [1], [9], [13], [15], [28]. Some synthetic grid papers that focus on more precise load modeling enhance demand estimation accuracy by considering the ratio of residential, commercial, and industrial loads at each substation [8], [29]. For Ghana, however, this is constrained by the lack of publicly available data.

The wide geographic variation in Ghana's electricity

[2]Note that some line flow limits had to be relaxed as discussed in Section 3.2 to obtain a feasible DC OPF problem.

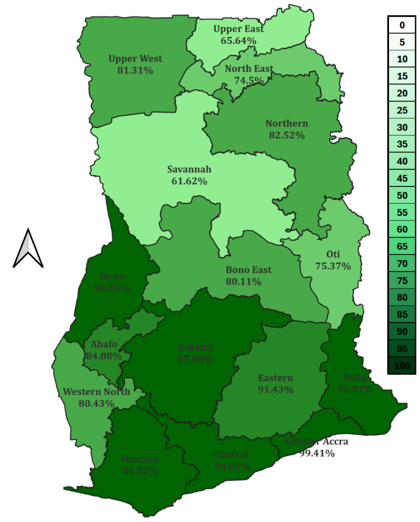


Figure 1: Share of the Ghanaian population per region with access to electricity [30].

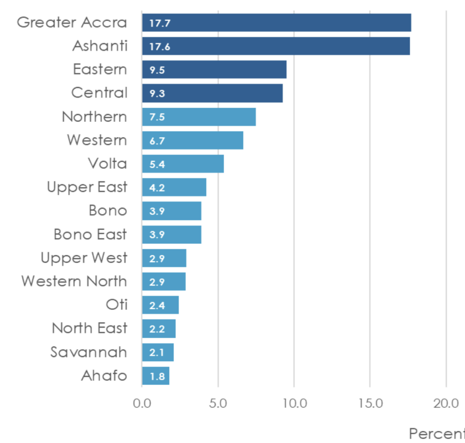


Figure 2: Ghanaian population distribution by region [31].

access rates poses a key challenge for load modeling using population-based methods. Unlike most Western countries, many towns and villages in developing countries remain largely un-electrified. Although the percentage of the Ghanaian population with access to electricity continues to grow, many regions lack full electrification, as shown in Fig. 1. As of 2022, 85.1% of the population had access to electricity [19]. These disparities suggest that population-based load modeling could lead to inaccurate results. To assess this, we used the available data to develop an alternative population-based model, as described next.

The most recent census in Ghana, the 2021 Population and Housing Census [31], reports a total population of 30.8 million and provides the numbers for the various administrative regions and districts; see Fig. 2. For the annual per capita electricity consumption, we use the value of 0.66 MWh as reported by the Ember Group report in [32] to compute the average active power consumption at each bus:

$$\text{Active Power Demand} = \frac{0.66\text{ MWh} \times \text{Population}}{8760\text{ hours/year}}.$$

We use a power factor of 0.95 for the reactive demands as per the Ghanaian renewable energy code [20].

Section 4 presents results from these computations and compares with accurate demand data from Ghana's Energy Commission [19] and Grid Company [17].

3.2. Estimation of transmission lines

The transmission system is characterized by the topology and line parameters. Instead of relying on publicly available utility maps and economic development databases, as in our prior work [14], we develop alternate models that estimate the grid topology using automated methods from the previous literature. To calculate the line parameters, we apply estimation methods from [1], [15], [33], [34] (as described in [14]) which 1) assign resistance, reactance, susceptance, and flow limit values based on line voltage level and length, and 2) calculate minimal line flow limit relaxations to obtain a feasible DC OPF solution. As described in [14], we compute these relaxations of the flow limits using a variant of the DC OPF problem where the line flow constraints include penalized slack variables. We also obtain bus name and voltage level information for all 99 buses using ECOWAS data as in [14].

Prior literature uses Delaunay triangulation as a geometric approximation for power grid topology, as it connects nearby neighbors and maintains a constant average nodal degree, both traits characteristic of real-world networks [1], [13], [15]. However, Delaunay triangulation tends to overestimate the average nodal degree, defined as $\langle k \rangle = \frac{2m}{n}$ (where m and n are the numbers of lines and buses, respectively), as around 6 [15], while real networks are typically less densely connected. For example, power grids in the western United States have $\langle k \rangle$ values from 2.5 to 3 [35]. With 99 buses and 160 lines, Ghana's actual grid topology used in [14] has $\langle k \rangle = 3.232$.

To create transmission topologies that better reflect Ghana's actual network, we adopt a combination of minimum spanning trees (MSTs) and Delaunay triangulation. Earlier work (e.g., [1]) primarily relies on Delaunay triangulation alone while more recent studies (e.g., [15]) introduce a more practical method that combines MST and Delaunay to produce a realistic topology that ensures connectivity of all buses while also achieving a desired average nodal degree. This process is described below in Sections 3.2.1 and 3.2.2. Ultimately, we create two alternate transmission topologies for sensitivity analysis and comparison purposes: a topology with an average nodal degree similar to the Eastern Interconnect in the United States [15] and a topology whose average nodal degree matches the actual Ghana network as used in [14].

Each bus is geolocated using latitude and longitude values estimated using Google Maps and OpenStreetMap. Buses at different voltage levels within the same substation share the same coordinates.

3.2.1. Minimum spanning tree generation For each of Ghana's standard transmission voltages (69, 161, and 330 kV), we created MSTs for all buses within Ghana [30]. Existing cross-border connections to substations outside Ghana were then added using the same connections as in the ECOWAS database. Additionally, since only three 225 kV substations are located within Ghana, as per [21], with most others at this voltage level being in neighboring countries, all existing 225 kV connections were included directly from the ECOWAS database, as with other non-standard transmission voltage levels.

The complete MST representation of Ghana's grid—consisting of one MST for each nominal voltage level (69, 161, and 330 kV)—has average nodal degrees $\langle k \rangle$ of 1.60, 2.00, 1.87, respectively, and an average $\langle k \rangle = 1.91$. While $\langle k \rangle \approx 2$, as expected for MSTs, the final MST representation also includes all existing 225 and 30 kV lines, as well as cross-border connections. MST algorithms were not used to estimate 30 and 225 kV networks, as few lines and substations are operating at these voltage levels within Ghana.

The MSTs are then augmented with selected lines from the Delaunay triangulation, as described below.

3.2.2. Delaunay candidate line selection The Delaunay triangulation gives a set of candidate lines for each voltage level. We then use a DC OPF formulation to calculate voltage angles θ using the same generation and demand parameters as our Ghana model from [14]. Additional lines are selected from the candidates using an iterative method similar to [15], prioritizing lines with higher estimated power flow $P_{exp,ij}$:

$$P_{exp,ij} = \frac{|\theta_i - \theta_j|}{x_{l,ij} \cdot d_{ij}}, \tag{1}$$

where i and j denote the line's terminal buses, $x_{l,ij}$ is the per-distance reactance of the line, and d_{ij} is the line length. Following [15] and [9], long-distance lines and lines parallel to existing lines at other voltage levels or increasing radial load are penalized. As per [36], select lines were penalized to reflect geographic constraints posed by the large Volta Lake in the central eastern region of the country. This Delaunay candidate selection process is intended to reflect the real iterative power flow analyses that grid planners use in expansion planning, balancing reliability and geographic constraints [15].

We created two alternate network topologies with differing average nodal degrees to assess how this quantity impacts accuracy. For our first alternate topology, we assume limited knowledge of Ghana's actual transmission system and hence seek to model the Ghanaian transmission system similarly to that of the United States. Accordingly, we added 2, 14, and 4 lines to the 69, 161, and 330 kV networks, respectively, to match with US network characteristics of $\langle k \rangle = 2.43$ [15]. This network is shown in Fig. 3b.

For our second alternate topology, we assume knowledge of the nodal degree distribution for the accurate Ghana network topology from [21] (used in [14]). To obtain the same nodal degree distribution for the various voltage levels, we add 64 lines to the 161 kV MST and 2 lines to the 330 kV MST; see Fig. 3c.

4. Numerical Results

This section empirically compares the synthetic models for Ghana's transmission system created using the automated methods discussed in Section 3 with the more accurate model from [14].

4.1. Change in electric demand

We first report the differences in the power demand between the two cases: the actual demands obtained from publicly available reports, as used in [14], and the population-based estimates discussed in Section 3.1.

The total demand between the two cases is relatively similar. According to publicly available reports [17], [19], the actual demand for the entire Ghanaian power system, at 2.648 GW, differs by 5% compared to the 2.516 GW obtained from the population-based estimate.

Despite the similarity in total demand, the spatial load distribution shown in Fig. 4 indicates more significant differences. The population-based demand estimate does not account for a large portion of the load demand from substations in the Greater Accra and Ashanti regions. This is possibly due to large industrial and commercial loads in these areas, which purely population-based modeling neglects.

These spatial differences can substantially impact the results of power system simulations. For instance, Table 1 shows the optimal costs for DC OPF solutions, with the population-based demand estimates yielding a 16.58% lower objective value due to differences in the generators dispatched. For example, approximately 130 MW less power is dispatched from the Asogli 330 MW natural gas power plant in the population-based demand case versus the report-based actual demand.

	Actual	**Estimated**	**Difference (%)**
Load (GW)	2.648	2.516	4.98%
Cost ($/hour)	66,760	57,266	16.58%

Table 1: Change in demand between the report-based actual and the population-based estimates.

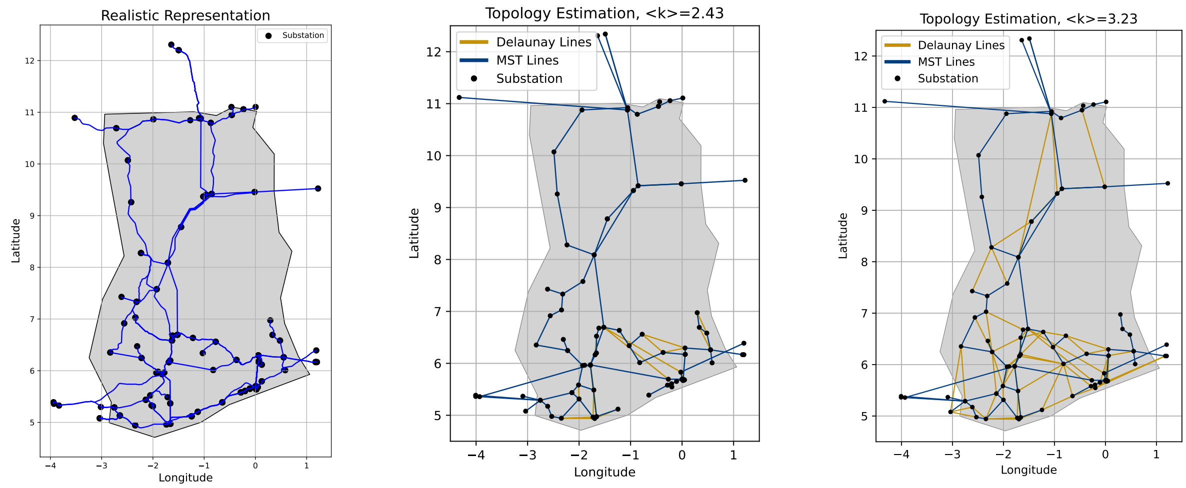
4.2. Change in transmission network topology

We next compare the actual grid topology of Ghana from the ECOWAS database [21], as used in [14], with the alternate topologies created via the MST and Delaunay triangulation methods discussed in Section 3.2

Note that the voltages in the Ghana transmission map from [17], [21] imply the presence of 14 transformers connecting buses at different voltages in substations when assuming one bus for every voltage level in a substation. The original version of the Ghana model, as described in [14], did not include these transformers; however, we subsequently added them, increasing the number of buses from 84 to 99. The following topological analyses focus solely on the transmission lines, excluding branches that represent transformers.

In Fig. 3, the ECOWAS network and the alternate networks largely resemble each other visually, with higher density in the south and sparse connections in the north. However, the alternate networks do not reflect the level of skewed connectivity present in the ECOWAS network as discussed in Section 4.2.2. Despite matching the overall connectivity of Ghana's network as represented by the average nodal degree $\langle k \rangle = 3.23$, the Delaunay candidate selection produces a less centralized network that does not have a high density of transmission lines between the Akosombo Dam and the Greater Accra Region in the southeast of Ghana, a characteristic present in the ECOWAS model and [17]. One possibility for this could be that Delaunay triangulation and candidate line selection do not allow for repeated selection of the same line. This does not reflect the ECOWAS test case, which has parallel lines at the same voltage level between pairs of buses.

4.2.1. Distribution of line flow limit relaxations As discussed in Section 3.2, when we lacked public reports that provided more accurate values, we estimated line flow limits using techniques from [1], [15], [33], [34]. To avoid infeasibility in the DC OPF problem when using these flow limits, our prior work in [14] employed an optimization formulation to compute minimum-size relaxations of the flow limits, ensuring the DC OPF problem remains feasible. We next analyze



(a) Base case representation of Ghana's transmission network using [17].

(b) Representation using US average nodal degree $\langle k \rangle = 2.43$.

(c) Representation using Ghana's average nodal degree $\langle k \rangle = 3.23$.

Figure 3: Comparison of Ghana's actual transmission topology from [17] versus algorithmically created networks.

the flow limit relaxations needed for various models.

Figure 5 shows the number of lines that require specific percentage relaxations to obtain feasibility. All three graphs indicate that the majority of the lines require less than 5% relaxation to obtain a feasible solution to the DC optimal flow problem. However, the specific relaxation varies for the different scenarios. With fewer lines in total, the flow limit relaxations for the $\langle k \rangle = 2.43$ model (Fig. 3b) are higher than the relaxations applied to the $\langle k \rangle = 3.23$ model (Fig. 3c), as shown in Fig. 5. However, both alternate models required less relaxation than the ECOWAS-based model from [14], with maximum relaxation just exceeding 50% instead of 100%. This is attributed to our line selection method, where Delaunay candidate lines were added iteratively based on expected power flow [15]. Consequently, we select lines with the highest power flowing through them, reducing the relaxation needed. Additionally, all lines in the alternate networks are idealized as shortest-distance connections between buses, regardless of local geography, while the realistic topology from ECOWAS models the actual winding of lines, resulting in longer lines on average. Nevertheless, all three networks have similar overall distributions of flow limit relaxations, with the vast majority of lines relaxed by less than 5%.

4.2.2. Nodal degree distributions As shown in Fig. 6, all three networks' nodal degree distributions exhibit a general downward exponential trend, consistent with real power networks [15], [35]. However, the skew in Fig. 6a reveals three highly connected outliers that are not typical in power network behavior observed in [15]—the Akosombo, Smelter II, and Volta substations are connected to 14, 17, and 22 lines, respectively. This reflects these substations' critical roles: the Akosombo Dam is a major hydroelectric power source in Ghana [30], while Smelter II and Volta—both located in Tema, an industrial hub in the Greater Accra region—serve areas with the country's highest electricity access rates [17], as shown in Fig. 1. These outlier cases cannot be easily accounted for in automated methods, such as MST generation and Delaunay candidate selection. However, the connectivity of these buses may be overestimated in Fig. 6c as we modeled one bus for each voltage level within a substation, which may not be the case in reality. For example, the Volta substation contains more than two buses and one $161/330$ kV transformer for its 330 kV and 161 kV voltage levels [17].

Furthermore, both the actual network topology from [14] and the $\langle k \rangle = 2.43$ alternate topology exhibit peak nodal degree values of around 2 to 3, which is consistent with real power networks in the United States [15]. Conversely, the $\langle k \rangle = 3.23$ alternate topology has a higher peak nodal degree of 4 in Fig. 6c. This is interesting because although the average nodal degree is the same in Figs. 6a and 6c, the actual network's average is skewed upward by outliers—its peak nodal degree is only 2. As a result, using this skewed-upwards average nodal degree for the $\langle k \rangle = 3.23$ alternate network produced a degree distribution that overestimates the system's connectivity. This is reflected by the clustering coefficient, $\langle c \rangle$, defined as the average of all c_i, the clustering coefficient for bus i [15]:

$$c_i = \frac{2e_i}{k_i(k_i - 1)}, \tag{2}$$

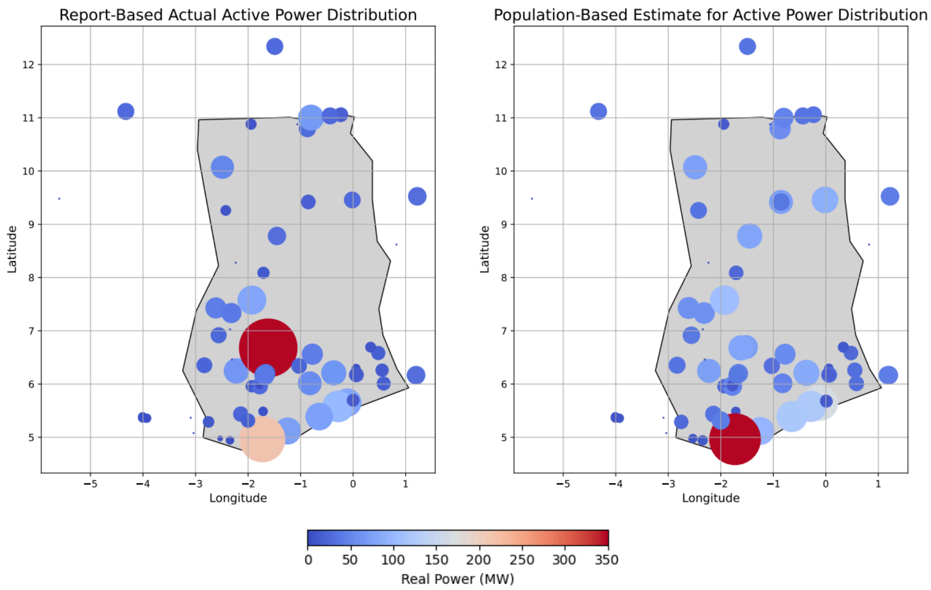


Figure 4: Comparison of actual and population-based loading scenarios.

where k_i is the number of neighbors of bus i and e_i is the number of lines between these neighbors. This metric characterizes the likelihood that two neighbors of a bus are also neighbors of each other, illustrating connectivity. The $\langle c \rangle$ of our realistic case, with 99 buses, is 13%, the higher end of the 1 to 15% expected for networks with more than 100 buses as reported in prior literature [15]. The $\langle c \rangle$ value for our $\langle k \rangle = 2.43$ alternate model is slightly higher, at 14%, still within the expected range, but our $\langle k \rangle = 3.23$ alternate model has $\langle c \rangle = 21\%$, overestimating the network's connectivity.

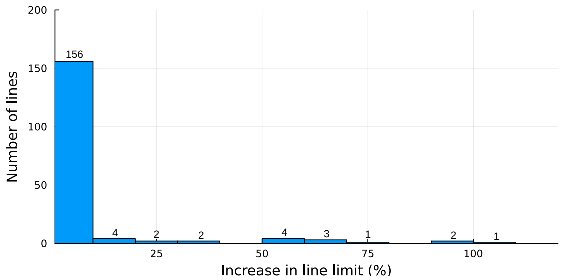
4.2.3. Delaunay separation of lines Another metric for assessing the similarity between networks is the degree of Delaunay separation. A line with Delaunay separation of one appears in both the actual and Delaunay network topologies. A separation of two indicates that two lines in the Delaunay model connect the actual line's endpoint buses.

In Fig. 7, the $\langle k \rangle = 3.23$ alternate network appears to be a better representation of the actual network topology used in [14] than the $\langle k \rangle = 2.43$ alternate network. 69.3% of the lines in the $\langle k \rangle = 3.23$ alternate network have a separation of one [14]. 98% of the lines have a separation of three or less, meaning a path of three or less edges in the alternate network connects 98% of each actual transmission line's endpoints—consistent with the average network behavior reported in [15], where this separation similarly reflects the geographic constraints of transmission system planning. In contrast, only 87.3% of the lines in the $\langle k \rangle = 2.43$ alternate network have a separation of three or less, with some separations reaching 19 hops in Fig. 7a. This suggests that using the nodal degree trends of Western networks is not as effective for modeling Ghana's topology, whereas incorporating knowledge about Ghana's nodal degree significantly improves the alternative network's realism.

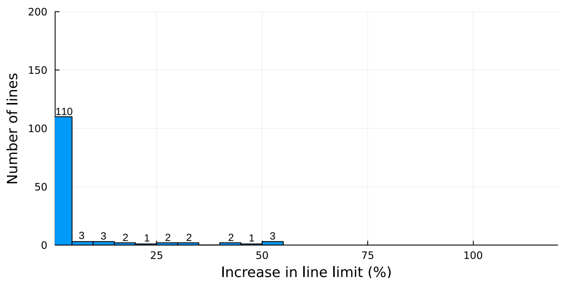
	Cost
Model from [14]	\$66,760/hour
Alternate model with $\langle k \rangle$ = 2.43	\$90,652/hour
Alternate model with $\langle k \rangle$ = 3.23	\$79,893/hour

Table 2: DC OPF results.

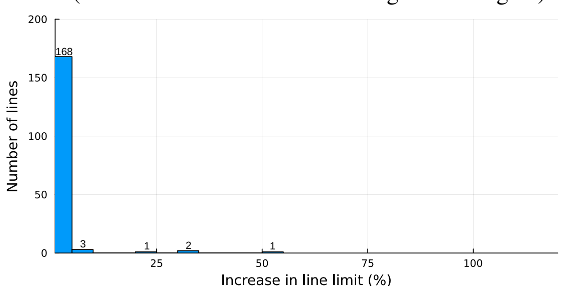
4.2.4. DC optimal power flow results Finally, as summarized in Table 2, we compare the DC OPF results obtained from the different models. We maintain the same generation and load parameters while changing the transmission topology among the three models. Using the $\langle k \rangle = 2.43$ alternate topology results in a 35.8% increase in the objective function of the DC OPF problem, while the $\langle k \rangle = 3.23$ alternate topology results in a less significant change in the objective function, with an increase of 19.7%. The latter result suggests that ensuring consistency in the average nodal degree more accurately captures the behavior of the actual Ghanaian transmission network. Conversely, the $\langle k \rangle = 2.43$ alternate topology (based on Western average nodal degree trends) least accurately reflects the actual Ghanaian network behavior. With Delaunay separations as large as 19 hops, the $\langle k \rangle = 2.43$ alternate topology exhibits poor spatial alignment with Ghana's actual transmission network. Due to sparser



(a) Flow limit relaxations for the model from [14] with Ghana's actual network topology.



(b) Flow limit relaxations for the alternate $\langle k \rangle = 2.43$ model (US Eastern Interconnect's average nodal degree).

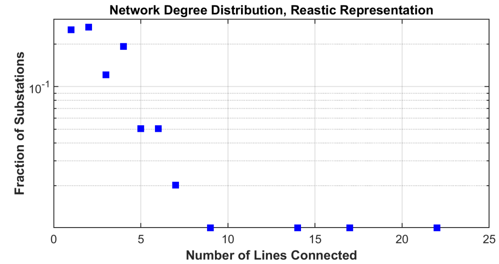


(c) Flow limit relaxations for the $\langle k \rangle = 3.23$ alternate model (actual Ghana network's average nodal degree).

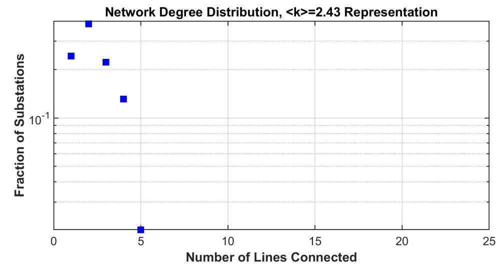
Figure 5: Line flow limit relaxations for DC OPF feasibility.

connectivity, power is likely forced through longer and more congested paths, resulting in significant cost increases in the DC OPF solution. Both alternate test cases have shortcomings in that they do not reflect the centralized nature of Ghana's actual network, with many parallel transmission lines to key locations. The absence of central hubs of high degree within the alternate test cases may contribute to the increase in the objective value of the DC OPF solution.

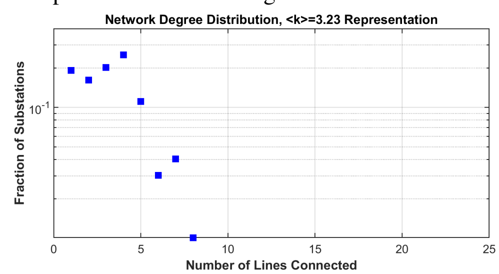
4.2.5. Discussion of key findings To summarize, the $\langle k \rangle = 3.23$ alternate topology offers both topological and operational realism, allowing it to closely match the model in [14] with the actual network topology. Conversely, the sparser $\langle k \rangle = 2.43$ topology results in significantly higher operational costs. This indicates that with knowledge about broad statistics of a network,



(a) Degree distribution for the model from [14] with Ghana's actual network topology. Observe the right-skewed pattern with three highly-connected buses.



(b) Degree distribution for the alternate $\langle k \rangle = 2.43$ model (US Eastern Interconnect's average nodal degree). Observe the steeper decline in node degrees.



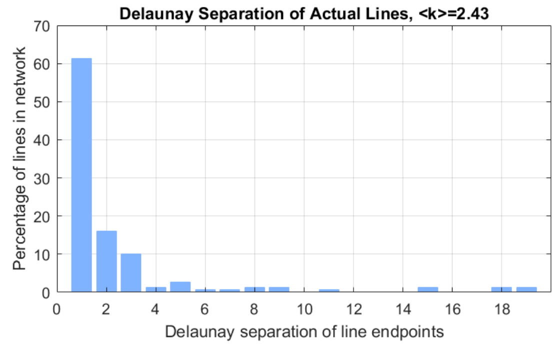
(c) Degree distribution for the $\langle k \rangle = 3.23$ alternate model (actual Ghana network's average nodal degree). Observe the more gradual exponential decline.

Figure 6: Logarithmic bus degree distributions exhibiting varying degrees of exponential decline.

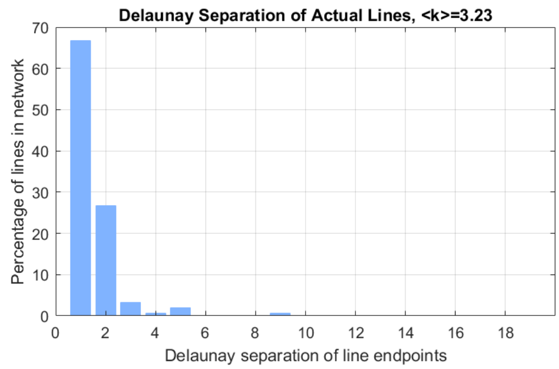
particularly a network's average nodal degree, Delaunay line selection can produce a significantly more realistic network. With general information on the nodal degree distribution and local geographic features, such as large lakes, our results for Ghana suggest that the use of MST and Delaunay-based line selection methods can produce networks that generally preserve key topological and operational characteristics for non-Western systems where complete data is not publicly available.

5. Conclusion and Future Work

This paper investigates the ability of existing synthetic grid estimation techniques to characterize the performance of real grid models accurately and efficiently. Using Ghana as a case study, we compare



(a) Delaunay separation of the alternate $\langle k \rangle = 2.43$ model (US Eastern Interconnect's average nodal degree) when compared with the actual network topology used in [14].



(b) Delaunay separation of the $\langle k \rangle = 3.23$ alternate model (Ghana's actual average nodal degree) when compared with the actual network topology used in [14].

Figure 7: Delaunay separation of transmission line endpoints in the generated representations of Ghana's 69, 161, and 330 kV network, in hops.

different methods for estimating power demand and transmission topology with our realistic grid model.

Our results show that while per capita electricity consumption provides a good estimate of the total system load, it may fail to fully characterize the spatial distribution of the load, resulting in inaccurate simulation results. Additionally, using topology estimation techniques such as the Minimum Spanning Tree and Delaunay triangulation can provide a reasonably accurate representation of the actual grid topology, particularly when specific selected network properties, such as average nodal degree, are available. However, these topology estimation techniques, while capable of matching the average nodal degree and overall shape of the network, did not capture the skewed nature of Ghana's power network, one that has more centralized hubs with high degree, rather than strictly following an exponential nodal degree distribution like other networks studied previously.

Our future work will investigate methods for circumventing data limitation challenges by creating more representative load distribution models that account for industrial and commercial loads, as well as examining how the electricity access rate may affect regional per capita consumption. We also plan to explore methods to allow multiple parallel transmission lines where appropriate, reflecting cases such as Ghana's grid, where multiple lines of the same voltage connect the same buses. Additionally, to further validate the results in this paper, we plan to create other synthetic grids to perform similar analyses. We present Ghana as the first step in a series of possible case studies to investigate the effectiveness of these estimation techniques in a global context.

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