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Journal
Proceedings of the IEEE, 107(9)

ISSN
0018-9219

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Publication Date
2019-09-01

DOI
10.1109/jproc.2019.2925759

Peer reviewed

INVITED PAPER

Distributed Resources Shift Paradigms on Power System Design, Planning, and Operation: An Application of the GAP Model

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ABSTRACT | Power systems have evolved following a century-old paradigm of planning and operating a grid based on large central generation plants connected to load centers through a transmission grid and distribution lines with radial flows. This paradigm is being challenged by the development and diffusion of modular generation and storage technologies. We use a novel approach to assess the sequencing and pacing of centralized, distributed, and off-grid electrification strategies by developing and employing the grid and access planning (GAP) model. GAP is a capacity expansion model to jointly assess operation and investment in utility-scale generation, transmission, distribution, and demand-side resources. This paper conceptually studies the investment and operation decisions for a power system with and without distributed resources. Contrary to the current practice, we find hybrid systems that pair grid connections with distributed energy resources (DERs) are the preferred mode of electricity supply for greenfield expansion under conservative reductions in photovoltaic panel (PV) and energy storage prices. We also find that when distributed PV and storage are employed in power system expansion, there are savings of 15%–20% mostly in capital deferment and reduced diesel use. Results show that enhanced financing mechanisms for DER PV and storage could enable 50%–60% of additional deployment and save 15 \$/MWh in system costs. These results have important implications to reform current utility business models in developed power systems and to guide the development of electrification strategies in underdeveloped grids.

KEYWORDS | Capacity expansion; distributed resources; electrification; power system modeling.

Manuscript received October 3, 2018; revised June 19, 2019; accepted June 26, 2019. This work was supported by the NSF CyberSEES Program under Grant 1539585. *(Corresponding author: Juan-Pablo Carvallo.)*

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This paper has supplementary downloadable material available at http://ieeexplore.ieee.org, provided by the author.

Digital Object Identifier 10.1109/JPROC.2019.2925759

I. INTRODUCTION

Power systems have evolved following a century-old paradigm of planning and operating a grid based on large central generation plants and transmission lines [1]. It was not economical to build these units in small sizes, and they had to be located far from load centers due to their environmental impact and resource availability constraints. This prompted the development of a hierarchical unidirectional network to move power to consumers, which led to the electric utility as we know it today. This paradigm is being challenged by the development and diffusion of modular generation and storage technologies. These systems are small and clean enough to be located very close to consumers and load centers, reducing the need for network infrastructure and suggesting that reframing of the hierarchical paradigm is possible.

There has been extensive research on the effects of distributed generation on the operation of distribution systems [2]–[6] and power systems in general [7]–[10]. Voltage regulation, protection issues, and power recovery coordination are the main operational challenges identified. In recent years, many studies have documented the new challenges on planning distribution system expansion with high penetration of distributed resources [11]–[13]. A related stream of literature has documented the tensions that distributed energy resources (DERs) create between transmission and distribution planning [14]–[18]. These studies suggest unpacking net demand into DER and load, redefining the boundary of both systems, and transitioning to comprehensive distribution–transmission planning processes and models. Despite these recommendations, there is no known research on how the whole power grid is designed, planned, expanded, and operated when modular resources are economically and technically competitive against large-scale centralized technologies.

This question is particularly relevant for power systems in regions with low electrification rates that could feasibly deploy these new technologies as an alternative to following the original grid extension paradigm. There is a growing literature that uses quantitative models to assess and recommend electrification strategies, their technological components, and costs (see [19]–[27]). However, these studies present several shortcomings; they treat the on- and off-grid decision as mutually exclusive, do not develop a temporal sequence of investments but a "snapshot" for the last year of analysis, do not include generation and transmission expansion, and assume that the existing power system is reliable, which is generally not the case in the regions where these models are applied. The model developed for and used in this paper addresses all these limitations by concurrently evaluating the distributed and centralized investment decisions in production and transmission of power across time and space.

There are over 1.1 billion people without access to electricity, a large majority of these in countries with very high levels of poverty [28]. Sub-Saharan Africa (SSA) is the most electrically disadvantaged region in the world with over 600 million people lacking access to electricity and hundreds of millions more connected to an unreliable grid that does not meet their daily energy service needs. There is an established relationship between electricity and energy consumption per capita and a host of well-being indicators, such as the Human Development Index, infant mortality, and life expectancy [29]–[31]. While the mechanisms through which electricity access benefit the population are not clear, there is a shared agreement that expansion in the capacity of consumers to use electricity will be key to lift populations out of poverty [32].

Expansion of the regional or national central grid has been a prevalent strategy for increasing electricity access in high- and low-income countries. However, in low-income nations, electricity from the domestic power system is unreliable[1]—particularly in rural areas—so it is not immediately evident how much value it adds to new users when (and if) they are connected [35]–[38]. Very poor urban and rural inhabitants that are credit constrained may need time to save money to acquire durable goods that translate into an increased demand for electricity [39]. Depending on tariff structures and connection costs, many poorer households may not even afford to connect to and/or consume from the electric distribution system even if they are close to it [40]. An expensive central grid expansion could be overshooting these customers and could be a suboptimal allocation of capital resources in these earlier stages. It follows that a very relevant policy question is whether new modular and decentralized technologies can be a better solution and what the appropriate balance of centralized and decentralized resources is.

Contrary to the current practice, we find that the following holds.

1) Hybrid systems that pair grid connections with decentralized PV, storage, and diesel generation are the preferred mode of electricity supply for greenfield expansion under conservative trajectories for future PV and storage prices.
2) When distributed PV and storage are not employed in power system expansion, average levelized cost of electricity (LCOE) increases by 15%–20% driven by increased diesel use and distribution grid expansion.
3) Specific financing for DER PV and storage could enable 50% of additional deployment and save 15 \$/MWh ($\sim$15%) in system costs.

These results have important implications to reform current utility business models in the developed power systems and to guide the development of electrification strategies in the underdeveloped grids.

This paper is organized as follows. We introduce the model in Section II. We then present scenarios and results from comparing a "traditional" system expansion against one with affordable and modular technologies that can be deployed at the distribution level (DER). This is followed by a sensitivity analysis on key parameters. We finally discuss these results and provide technical and policy recommendations.

II. METHOD

We develop a capacity expansion model with an explicit representation of transmission and distribution networks: the grid and access planning (GAP) model. GAP has the ability to concurrently decide whether to expand the transmission and distribution systems and whether to deploy decentralized and/or utility-scale generation and storage resources to meet demand at prescribed levels of reliability. GAP is based on the SWITCH capacity expansion model developed at the Renewable and Appropriate Energy Laboratory, University of California at Berkeley (UC Berkeley)

[1]For statistics in Africa, see [33]–[35].

[41]–[47]. The SWITCH model is described in detail in the supplementary material.

The GAP model should be used as a high-level planning tool by policy makers, and regulatory staff and utility planners who seek to understand the interactions between demand- and supply-side resources and their evolution over time. The model is not intended to produce investment decisions for network or resource procurement. The model creates internally consistent and reasonable least-cost expansion scenarios that can be ported into production cost and simulation models for a deeper level of analysis. This reduced technical accuracy is necessary for the computational tractability of the joint operation and investment of the whole power system.

Jurisdictions that allow vertical integration can particularly benefit from a joint generation–transmission–distribution model, such as GAP. This is the case of almost all of SSA, portions of Asia and about half of the United States [48], [49]. However, even in regions where joint ownership of generation and distribution assets is limited, system operators can benefit from an integrative assessment to use rate design and incentives to guide the adoption of distributed resources [50].

In this paper, we develop and implement the GAP model to explore the conditions that affect the adoption of centralized and decentralized resources in the developed and undeveloped power systems. In particular, the distribution system, including node demand representation, is conceptual and represents a typical emerging economy medium-voltage (MV) system. The implementation in this paper borrows some basic parameters, topologies, and assumptions from the SWITCH-Kenya model to reflect the conditions in emerging economies [41]. We choose this approach to study broad questions on power system development with low-cost distributed resources and produce generalizable results for power system planning and electrification strategies based on a choice of plausible assumptions and parameters. In this section, we introduce the model in generic terms. In Section II-A, we discuss the Kenya-specific data sources that we use to parameterize the model.

A. Model Overview

GAP is implemented as a linear program whose objective function is to minimize the net present value of the capital costs from investing in generation and storage units, transmission lines, distribution grids, and DER, plus the operational costs to run and maintain these systems. The GAP model meets all or part of the demand at every node on every time step by installing and dispatching utility-scale and distributed resources, and the required transmission and distribution infrastructure. Generation operation constraints reflect different types, such as baseload, flexible baseload, peakers, and variable nondispatchable. Transmission and distribution systems allow bidirectional flows, but there is no feedback allowed from the distribution to the transmission system. The model enforces spinning and nonspinning reserves that can be provided by utility-scale, distributed, and storage resources. The model can be configured to enforce constraints related to renewable energy targets, emission caps, reliability levels (% demand met), and level of end-use satisfied demand. Several “conservation” constraints assure that the basic power system physical performance is adequately represented. A mathematical representation of the model is available in the supplementary material.

B. Spatial Resolution

The GAP model represents an approximate primary distribution system by solving a network flow problem on a set of possible connections with supply and demand available on each node (see Fig. 1). There is a single distribution system for each “load zone.” Here, we define a load zone as the spatial region served by a single node in the modeled transmission system. Each load zone is represented by a “head” node that is electrically equivalent to a stepping-down trunk substation (see the red dots in Fig. 1). Existing and new potential utility-scale generation is connected directly to this head node by dedicated transmission lines. The remaining nodes are “distribution” nodes, although we refer to them as “nodes” throughout this paper (see the black dots in Fig. 1). Distribution nodes are randomly positioned in space in this implementation, but with more detailed data, they could represent the existing villages, cities, distribution transformers, MV segments, or other features and topologies at the distribution level. Nodes are connected by “distribution links” that are analogous to MV circuit segments and possess length, losses, and capacity attributes. Distribution links can represent the existing MV lines or prospective lines that do not exist, but the model could choose to expand as part of the optimization.

C. Temporal Resolution

The model runs for three five-year investment periods: “2020” (2017–2022), “2025” (2023–2027), and “2030” (2028–2032). On each period, the model makes investment decisions to install utility-scale or distributed generation, distributed storage, and to expand any of the transmission lines or install and expand any of the distribution links. Both utility scale and distributed storage are represented by a discharge capacity in MW and a storage capacity in MWh. The model represents days by sampling every 3 h, for a total of eight daily representative and chronological hours. Two days per month are selected for sampling—a peak day and a median day—that are weighted to reflect total energy demand for a given month. Four months are simulated per investment period, roughly representing all possible seasons in a given year. In this way, the model simulates 3 [periods/simulation] $\times$ 4 [month/period] $\times$ 2 [day/month] $\times$ 8 [hours/day] $=$ 192 [hours/simulation]. This sampling approach makes

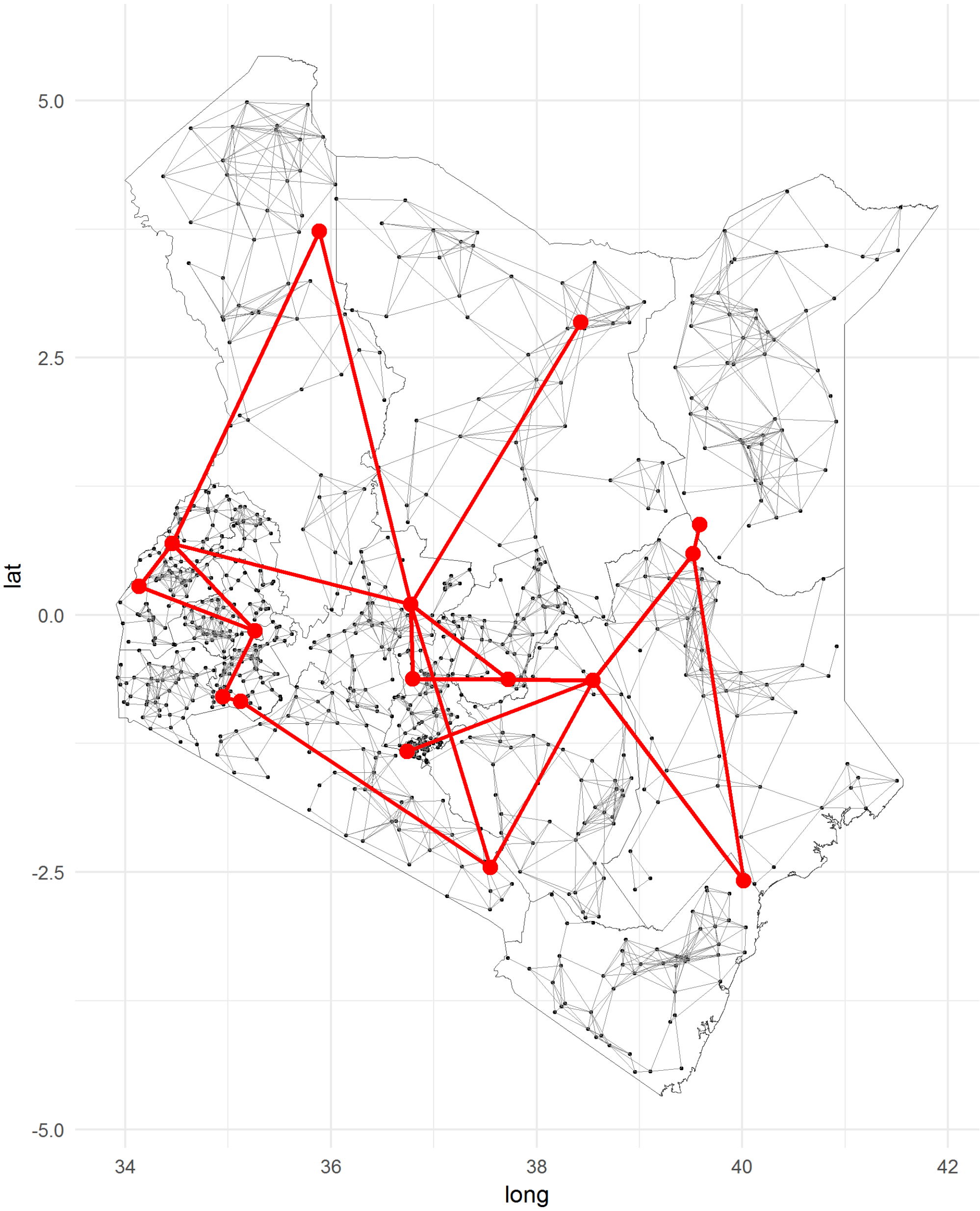

Fig. 1. ***GAP model network implementation, including existing trunk transmission substations and lines (in red), distribution nodes (in black), and potential links between nodes (gray).***

the modeling computationally tractable, which is not possible if all hours were used.

GAP jointly optimizes investment and dispatch costs by running a merit-order hourly dispatch to meet desired levels of demand in each of the 192 simulated hours. The model performs a joint dispatch of utility-scale and decentralized generation/storage and transmission and distribution line flows, all subject to the available installed capacity on a given period. Storage dispatch decisions include charging and releasing of energy as well as a variable to track energy stored. The only distributed generation technologies that are not dispatched are the PV systems and the lighting-only solar home system (SHS). The latter is considered fully available at night hours from 7 P.M. to 1 A.M. with zero marginal cost. The flows on transmission and distribution networks are the result of generation and storage dispatch decisions and are estimated using a transportation-flow model due to computational restrictions and nonlinearity of power flow models with investment variables. While simplified, research has shown that transportation models' network investment decisions do not differ significantly from those based on dc optimal power flow models [51], [52]. Reactive power is not modeled directly, but sensitivity scenarios for distribution system costs and energy losses indirectly reflect the cost and operational impacts of reactive power management technologies deployed in actual distribution systems.

D. Demand

To simulate conditions prevalent in many constrained power systems present in emerging economies, the model includes a "decision to consume" variable that represents how much demand is satisfied on a given node and hour for a specific end-use and customer class (residential, commercial, or industrial). The model could potentially minimize costs by not serving any demand if this variable was left unconstrained.[2] The difference between the final value of this variable—realized demand—and the original or "latent" demand is the energy not served (ENS), a typical reliability metric [53]. The ENS is a metric that links system reliability with its worth [54]. The ENS could be included in the objective function if an appropriate value of lost load (VoLL) is available to quantify the cost of not serving demand. As there are no known VoLLs estimations for emerging economies, we do not include VoLL as part of the cost minimization in this implementation of the GAP model. The expected value of outages in generation, transmission, and distribution is included by a de-rating factor on their available capacity. A stochastic representation of outages is outside the scope of the model.

This "decision to consume" variable can be interpreted and used in different ways. First, it can be constrained to fulfilling certain end uses for specific customers (i.e., meet all residential lighting demand). This setup can be used to study the cost and distributional effects of policy targets. Second, this variable can also be set to meet system-level reliability standards to understand the expected temporal and spatial allocation of shortages. Finally, the node-level values for this variable reflect the optimal allocation of consumption among types of customers and/or energy services.

Each node has a mix of residential, commercial, and industrial demand. The head node has a larger allocation of industrial demand representing higher voltage consumers that do not directly affect the remaining distribution system. Industrial and commercial demand profiles are characterized by a single representative daily consumption curve. Residential demand is split into different end uses or energy services. End uses are represented by specific daily consumption curves (e.g., lighting is only used in the evening and early morning). With this specification, we can study costs and timing involved in achieving end-use-based electrification goals, such as minimum lighting-level provision, access to refrigeration, or access to entertainment, among others. We can also assess how different services are fulfilled under nonperfect reliability conditions. Representing demand through energy services also helps understand how customer preferences—reflected in the inputted demand profiles—affect system costs.

[2]We actually verified that leaving this variable unconstrained in a cost minimization setup leads to no demand being met, an expected but important result for model consistency.

E. Technology Options

At the utility scale, the model has natural gas combined-cycle gas turbine (CCGT) and simple-cycle combustion turbines (SCCT), diesel peakers, pulverized coal, run-of-river hydropower, and geothermal, solar PV, wind, and battery storage technologies available for installation. At the distributed scale, the available technologies are diesel generators, solar PV, battery storage, and SHSs. For distributed solar PV, we use the same radiation data employed in the utility-scale plants to estimate an average radiation at the load zone level, although the model supports node-level values if needed and available. Finally, SHS is configured to meet lighting and charging demand only; it cannot be used to meet demand from other end-use services. This is to supply the most basic access level (Tier 1) as defined in the World Bank's Multi-Tier Framework [55].

III. SETUP/PARAMETERIZATION

The version of the model implemented in this paper uses 16 load zones connected between themselves by 23 transmission lines whose location and capacity are based on an aggregation of the existing Kenyan transmission system. Fig. 1 shows the portfolio of distribution system nodes and links in all load zones. In this greenfield study, we initialize the model without distribution lines; candidate internodal connections or "links" are generated with a random graph algorithm. The density of the random graph can be chosen arbitrarily, but our calibration determined that an average of five candidate links per distribution node was an adequate balance of computational capacity and system representation (see the details of the random graph creation in the supplementary material). With this density of candidate links, both radial and fully meshed solutions to the optimization algorithm are possible. We initialize each zone with 50 nodes and between 140 and 190 bidirectional links per load zone, for a total of 800 nodes and $\sim$2900 possible MV segments in the model. For reporting purposes, load zones are classified into three categories according to their density: high, medium, and low (also referred to as sparse). Density is based on load zone surface area and population for Kenya according to the 2009 census. Load zone surface area differences translate into different inter-nodal distances. Mean distance between the nodes is 12, 28, and 44 km for high-, medium-, and sparse-density areas, respectively. There are over 79 000 km of possible links that the model can choose to expand.[3] The distribution system in this simulation will be the result of investment choices in expanding any of the available 2900 links and/or installing decentralized resources.

[3]As a point of comparison, the Uganda medium-voltage system had an aggregate length of 16 590 km as of 2017.

Numerical parameters at the generation level include fuel and capital cost projections for each technology, variable nonfuel and fixed costs, and hourly capacity factors for each wind and solar site. At the transmission level, the main parameter is the extension cost, set at 1000 \$/MW-km based on [41]. A complete list of numerical parameters at the generation and transmission level is provided in the supplementary material.

At the distribution level, relevant numerical parameters include distribution system losses, grid extension costs, capital cost of distributed resources, and diesel fuel costs. Though losses are a nonlinear function of power flow, to preserve the linear structure of the mathematical program, we model losses as linear inefficiencies that are proportional to distance and delivered energy. We employ a benchmark of 15% losses per 100 mi of distribution line applied to the segment distance. Base distribution grid extension costs are set at 35 000 \$/MW-km, which we derived from actual project development documents obtained from the Kenya Rural Electrification Authority. This value varies substantially across case studies and analyses in other countries. Other electrification studies have used values in the 2000–8000 \$/MW-km range [25], [27]. Therefore, we test a range of expansion cost values from 2000 to 35 000 \$/MW-km as sensitivities. Costs for distributed storage, PV, and diesel generators are set at 1.5, 2.5, and 1.5 times the corresponding value for their utility-scale equivalent, respectively. This relationship guarantees the consistency between potential utility and distributed scale technology cost variations. Diesel fuel costs vary by load zone, but without more detailed local pricing information, we assume that the distributed level fuel costs are the same as the utility scale for a given zone. Diesel generators have the same capital cost in \$/kW in any place, but fuel costs vary by load zone according to the premium paid for transportation estimated in the 2015 LCPDP. Capital costs for all technologies and fuel costs come from the SWITCH-Kenya model [41]. See Table A1 in the supplementary material for values used in this simulation.

For this paper, we implement a simplified model to create hourly demand forecasts and to allocate loads to nodes. Residential sector demand is split in five end uses: lighting, television, refrigeration, ironing, and other large appliances (washer, dryer, or air conditioning). Each appliance or end use is represented by a 24-h demand profile sampled every 3 h to match model daily resolution. Homes are segmented in three socio-economic levels and each level is endowed with a portfolio of appliances and a level of consumption, based on the data from the 2005/2006 Kenya Household Budget Survey (KHBS). Each node has a specific initial share of households on a given socio-economic level, ranging from 0% to 5% for high consumers, from 10% to 30% for medium consumers, and the remainder for lower level consumers. We represent the intensive margin as consumers moving into the next consumption or socio-economic level based on income increases derived from the GDP growth forecasts from the World Bank. The extensive margin is represented by population growth per node. This means that the share of consumers by node changes on each investment period. We calibrate and verify the consistency of the residential demand forecast by calculating annual energy consumption, peak demand, and load factors and compare them with values reported by the domestic Kenya utility, Kenya Power. Commercial and industrial forecasts are based on allocating into nodes existing projections used in [41] and derived from the domestic Kenya sources. Commercial demand is allocated in proportion to the population represented by each node. Half of the industrial demand is allocated to the head node, and the other half is allocated randomly to the remaining nodes. We use a 24-h demand profile to represent temporal consumption patterns for each segment. For simplicity, the demand profile for industrial and commercial customers does not change with seasons or investment periods. We calculate that the commercial and the industrial load factor are 55% and 73%, respectively, which is in line with typical values for this metric.

The GAP model is implemented in AMPL and solved with CPLEX 12.0 on a server with four Intel Xeon processors running at 3.33 GHz and 32 GB of RAM. Depending on the setup, the model solves approximately between 10 and 13 million variables using a barrier algorithm with no crossover. The crossover simplex/dual iterations were computationally intensive, possibly due to numerical instability, and took between 80% and 90% of the solution time. To address this, we performed several test runs using simplified versions of the model to compare solutions with and without crossover. No-crossover solutions were acceptable for our purposes in terms of possible infeasibilities and suboptimality. Simulations used for this paper took between 90 and 120 min each to solve.

IV. SCENARIOS

As with any forward-looking model, GAP has little to no information to use for calibrating its output. The best use of these types of models is for scenario analysis. This analysis is focused on assessing the types of power systems and overall expansion strategies that are optimal under a scenario with affordable modular generation and storage that can be located close to load centers. We then create a "traditional" expansion scenario in which grid extension and diesel generators are the only resources that can be used to supply distribution loads. We use this scenario as a benchmark to assess different electrification routes that employ other technologies and that are subjected to different constraints. These sets of scenarios are summarized in Table 1.

The "BAU w/o DER" and "BAU w/DER" cost minimization scenarios are compared and used to evaluate the impact of a full suite of technological options for distribution system expansion. The "BAU w/o DER" scenario

Table 1 Summary of Scenarios

Scenario code	Distributed PV-Storage allowed?	Description
BAU w/o DER	No	BAU scenario with no pre-existing transmission and generation, which allows only grid extensions and distributed diesel generation to supply distribution nodes
BAU w/o DER GridExt	No	Identical to above with grid extension costs sensitivity at $2000, $10,000 and $20,000 per km-MW. Default is $35,000 per km-MW
BAU w/DER	Yes	Identical to BAU w/o DER, but allows distributed PV and storage.
BAU w/o DER Sys	No	BAU without DER, including the existing transmission and generation system in Kenya.
GridExt	Yes	BAU w/DER with grid extension costs sensitivity at $2000, $10,000 and $20,000 per km-MW. Default is $35,000 per km-MW
Losses	Yes	BAU w/DER with losses parameter sensitivity at 3%, 5%, 10% and 15% per 100 mile of distribution line. Default is 15%.
LowBatLife	Yes	BAU w/DER with battery storage life reduced to 5 years. Default is 15 years.
LowDGCost	Yes	BAU w/DER with and lower capital costs for PV and storage. PV now reaches 1013 $/kW by 2030 and storage reaches 90 $/kWh by 2030. Default is 1900 $/kW and 309 $/kWh by 2030, respectively.
LowOff	Yes	BAU w/DER with 1% annual real financing rate for distributed PV, storage, and SHS. Default is 7%.
HighOff	Yes	BAU w/DER with 15% annual real financing rate for distributed PV, storage, and SHS. Default is 7%.

replicates the "traditional" expansion paradigm using central grid extensions and distributed diesel generation only. However, neither of these scenarios represents the existing distribution, transmission, and generation infrastructure. Therefore, we develop an additional scenario, "BAU w/o DER Sys" in which we include the existing generation and transmission infrastructure available from the SWITCH-Kenya model to test its impact on system expansion results.

The next five scenarios are sensitivities on key parameters. The "GridExt" cost minimization scenario is used to analyze the sensitivity to distribution grid extension costs. The "Losses" scenario studies the effect of different distribution system losses' parameters. During our exploratory analysis, we identified these two variables as the most impactful and with the highest policy implications. We then explore two key technology sensitivities. "LowBatLife" assesses the impact of reduced battery storage lifetime due to potential frequent cycling and regulation. "LowDGCost" explores the effect of the most optimistic capital cost reductions for distributed PV and storage. Finally, in "LowOff" and "HighOff" scenarios, the financing rate for distributed PV and storage is set at 1% and 15% real annual, respectively. Financing rates could be substantially affected by effective policy intervention to pool customers and improve creditworthiness. We then test the impact of public financing at social rates versus more expensive private financing on system expansion decisions and costs.

V. RESULTS

The results are presented in two sections. In Section V, we use the GAP model to understand the impact of investment decisions, costs, and system efficiency of DER adoption on power system expansion by: 1) comparing system expansion with and without the existing generation and transmission infrastructure; 2) examining and explaining supply investment choices; 3) studying the impact of DER in system efficiency and capital deferment; and 4) assessing the cost impacts of DER availability and adoption.

In Section VI, we assess the robustness of the results from Section V through sensitivity analyses of key parameters. Generally, the results are reported for the three node density categories—high, medium, and sparse—and in some cases for the three investment periods—2020, 2025, and 2030.

A. Existing Transmission and Generation Infrastructure Have Little to No Influence on System Expansion by 2030

We first simulate the expansion for a power system with no pre-existing infrastructure and limited technology alternatives. Only diesel generation and distribution system extensions can be used to supply retail consumers, in addition to expanding transmission and utility-scale generation. This scenario replicates the century-old paradigm for least-cost power system expansion based on grid extension and diesel generation for off-grid areas. In addition, we run an identical scenario that includes the pre-existing generation and transmission infrastructure installed in Kenya as of 2015. We compare that the results for both of these scenarios to find the resource allocation decisions are almost identical.

B. Availability of Distributed PV and Storage Dramatically Changes Supply Choice and System Evolution

We study the "traditional" expansion with no pre-existing system and find that between 75% and 80% of supplied energy comes from utility-scale resources,

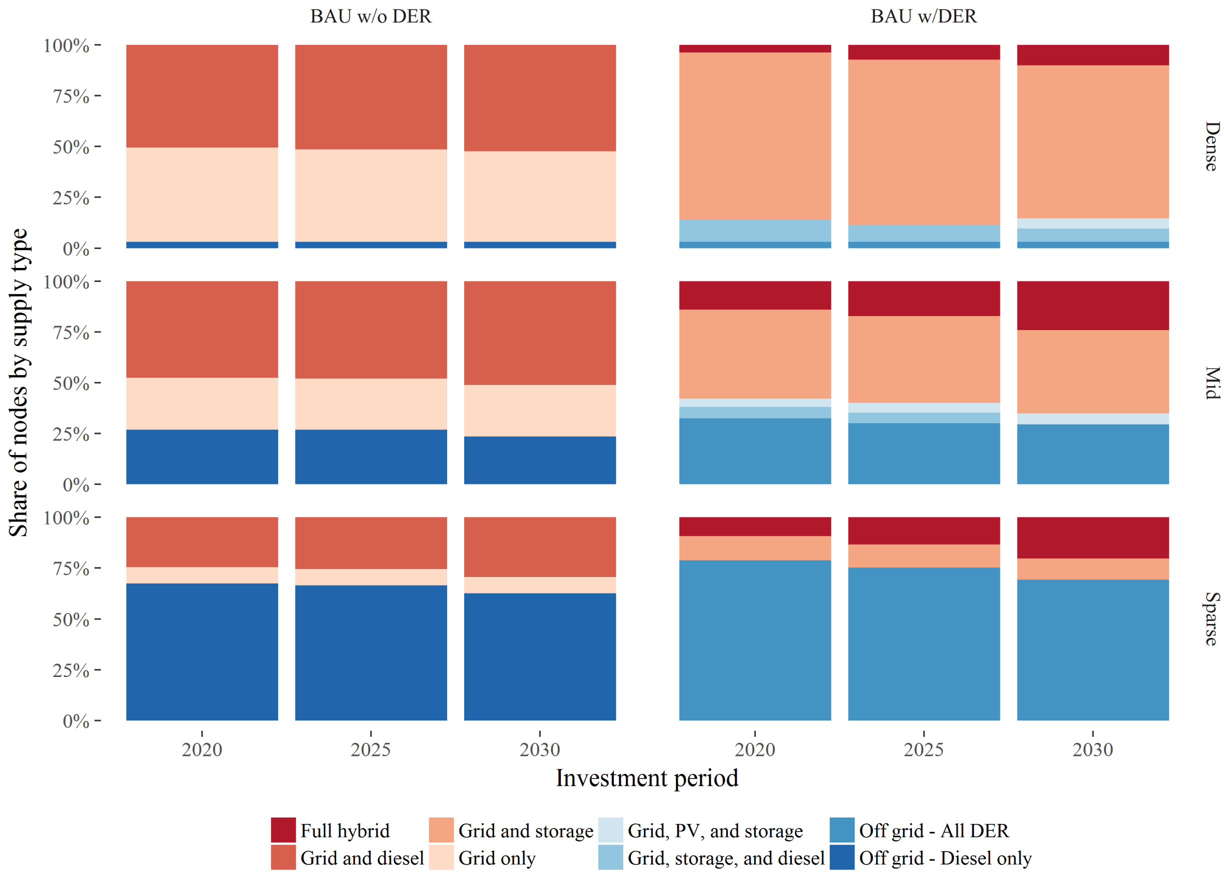

Fig. 2. ***Share of nodes by supply mode and load zone density category for least-cost expansion with (right) and without (left) new distributed technologies.***

while 20% comes from distributed diesel generators. However, about two-thirds of the nodes have diesel generators installed and half of those nodes are connected to the distribution system in "hybrid systems" [see Fig. 2 (left)]. Even in dense load zones, over half of the nodes have diesel generators installed even if these nodes are connected to the distribution system. Hybrid systems are the most common arrangement in load zones with medium density, while in sparse areas, over 75% of nodes have diesel generators in the off-grid mode and 20% are supplied with a grid-diesel hybrid mode. The prevalence of diesel generation in the "traditional" expansion is consistent with underbuilt and unreliable power systems, as this is the case of Nigeria, especially if all demand must be met [56]. In addition, high connection costs make any distributed generation resource more cost-effective. Distributed diesel generation capacity in a scenario with low expansion costs is two-thirds of that in the BAU case and its production is four times less (see Fig. A17 in the supplementary material).

The role of diesel to meet peak demand explains the difference between diesel deployment and production (see Fig. A1 in the supplementary material). In dense zones where diesel generation is installed, it is exclusively used to meet peak demand in the evening hours. In medium-density areas in peak hours, about half of demand is met with diesel generation. However, in off-peak hours, less than 10% of demand is met with this resource. In sparse areas, only the nodes closest to the trunk substation are grid-connected. Consequently, on average, about 80%–90% of peak demand is served by diesel generation in an off-grid mode.

The expansion decision mix changes substantially with the presence of modular PV and storage systems that can be installed at the distribution level [see Fig. 2 (right)]. When affordable decentralized resources are available, there are no grid-only nodes in the simulations. Of the 60% nodes with grid connection, half of the nodes have distributed storage. Nodes that install all possible resources grow from ~5% in 2020 to 15% by 2030 as PV becomes more affordable and is added to these hybrid systems. In addition, the share of off-grid nodes increases slightly from ~20% to ~25%. As opposed to the "traditional" expansion scenario, these nodes are supplied by a mix of PV, storage, and diesel generation. The similarity in the share of off-grid nodes suggests that the decision to connect nodes to the

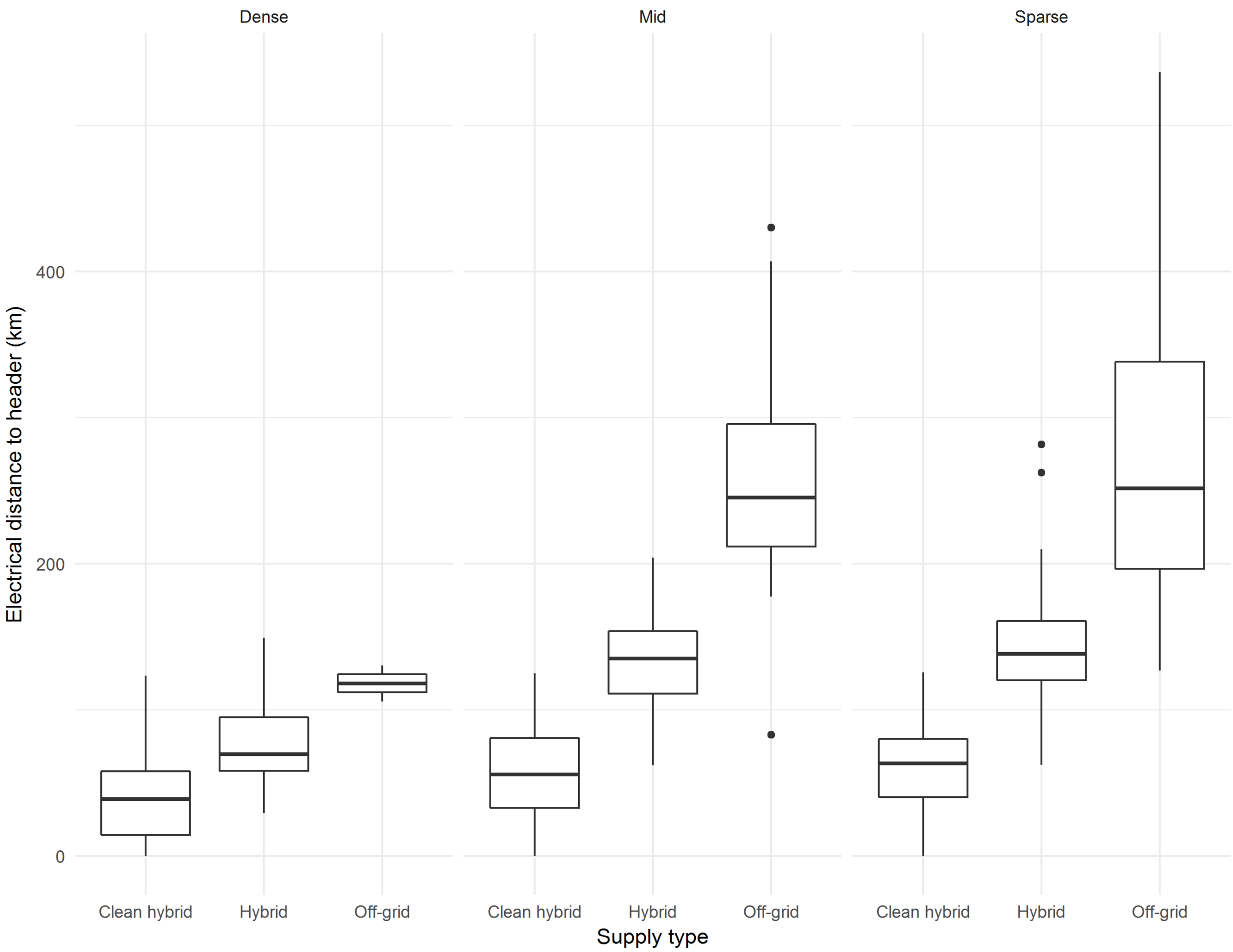

Fig. 3. ***Supply mix for three load zone density categories as a function of distance to the feeder header.***

grid depends largely on topology rather than technology alternatives. We examine this hypothesis in more detail later in this paper when performing sensitivity analysis.

Storage availability and operation is particularly critical in shaping these new power systems. In sparse and medium-density areas, batteries are used to store PV production at high irradiance hours and to release in the evening (see Fig. A2 in the supplementary material). In sparse areas, about 90% of peak demand is met with storage discharge. However, in dense areas, storage is charged at night from the grid and released through the day to meet up to 30% of evening peak demand. This mode of operation influences the decision variable for storage discharge duration. There is a mean of 5 h of storage in high-density areas and 2 h of storage in medium-density and sparse areas, which correlate with the optimal storage dispatch in each area.

C. Distance to the Transmission System Is Correlated With Nodal Supply Mix

We study the correlation between the electrical distance of a given node to the header and the type of supply mix for that node for the scenario with DER (see Fig. 3). For illustrative purposes, we use a minimum spanning tree to assign a distance to nodes that are not connected to the distribution grid and include them in this analysis. We find a relatively clear median distance threshold for each of the three supply modes and load zone density categories. Clean hybrid nodes are usually located within 50–70 km of the head node on all three density categories. Hybrid nodes—nodes supplied by a combination of grid and all DER including diesel—are more prevalent at the distances of 70 km in dense areas and 100–150 km in medium- and low-density areas. Off-grid nodes only become cost-effective at median distances above 200 km from the feeder head, although there are off-grid nodes located as close as 120 km in medium- and low-density areas.

One possible explanation for the supply distance relationship is that closer nodes can be reached by larger capacity grids that are economically dimensioned to meet peak demand. For nodes located at longer distances, it becomes more cost-effective to meet peak demand locally with a mix of dispatchable diesel and storage and build grids with less capacity that are operated

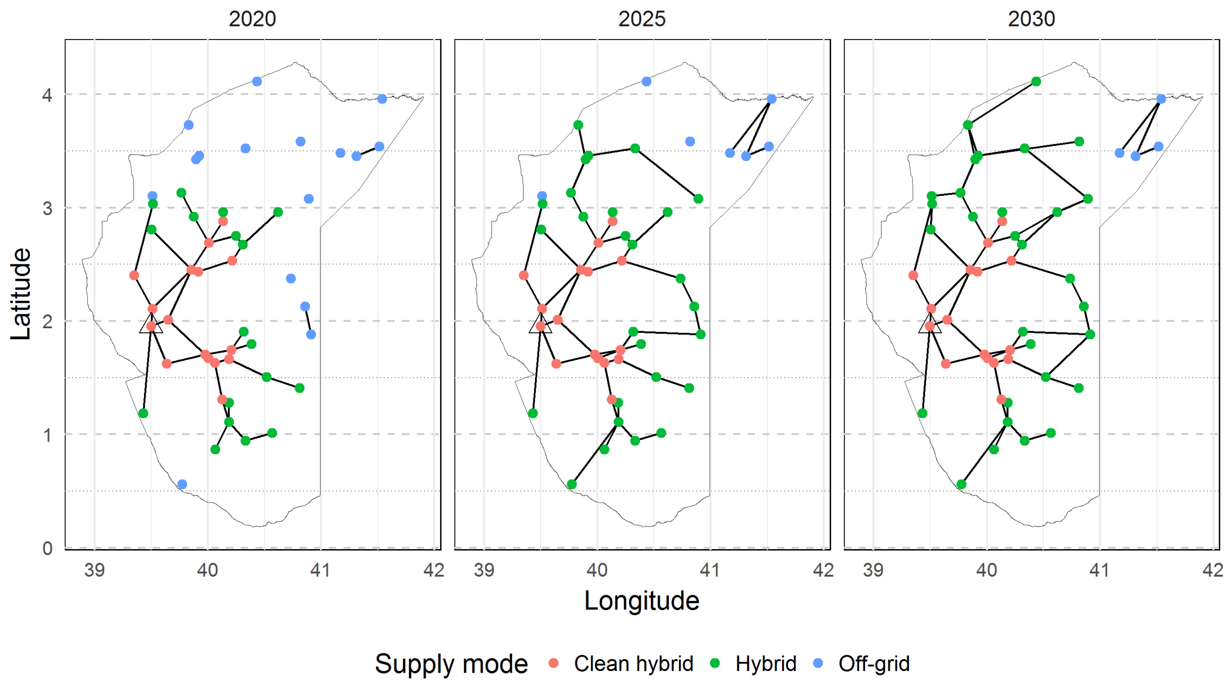

Fig. 4. ***Electrification sequencing decisions for a low-density load zone in northeast Kenya.***

with higher load factors. We find evidence of this by examining the link utilization factor (LUF).[4] In systems with no DER, LUF for nodes farther from the head node is lower than that for closer nodes. However, in systems with the substantial deployment of distributed resources, LUF is higher for links farther from the head node (see Fig. A6 in the supplementary material). This is because when DERs are available, distribution system's links are sized to carry baseload from the grid, and the locally deployed DERs are used to meet peak demand.

The electrification studies within the energy access literature have focused on thresholds to declare areas as off-grid and suggested the share of population or load that would be more efficiently served off-grid. Reference [27] reported that 15% of total electricity is delivered through off-grid systems in their simulations for Kenya. Reference [19] found that less than 10% of households could be cost-effectively supplied by decentralized solar PV in a case study for Ethiopia. Reference [25] found that in a full penetration scenario for Kenya, 7% of households would be supplied off-grid. None of these studies allowed for hybrid systems, nor do they simulate transmission and generation capacity expansion. In the GAP model, about 31% of nodes are supplied off-grid when DERs are available and 26% of nodes are supplied off-grid when distributed solar PV and storage are not available. The difference is because distributed PV and storage are more cost-effective than diesel, which makes their joint deployment in hybrid supply modes a least-cost solution. Off-grid nodes are more common in lower density areas than high-density areas. Nodes are off-grid when located beyond 100 km in low-density zones and 150 km in medium-density zones, with no off-grid nodes in high-density zones. This is explained by the relatively higher demand and shorter inter-nodal distance in medium-density zones compared with low-density zones, which makes grid extensions relatively more cost-effective in the former.

The sequencing of electrification decisions is a unique feature of GAP that highlights the relevance of system expansion dynamics in regions with low electricity access. As a case study, we study a low-density zone and map the modes of supply and grid extension decisions for a least-cost scenario with perfect reliability (see Fig. 4). In the first period (2020), about two-thirds of the nodes are connected to a distribution system; the remaining third operates in the off-grid mode with PV + storage + diesel systems. There are two minigrids built which interconnect two nodes in isolation. The grid-connected nodes closest to the feeder head have only distributed storage installed. Farther connected nodes have PV and storage, and the nodes at the edge of the distribution system also have diesel generators. This is a strategy to save on losses and grid capacity for nodes that are distant, especially because distant nodes require all the systems to be sized to meet their demand. The next period (2025) is characterized by grid extensions with little change in node-level supply modes. Most off-grid nodes with the

[4] The LUF is the ratio of average demand to line capacity for a given line segment, in an equivalent way as load factor is defined for loads. The LUF is used to measure the efficiency in line segment utilization.

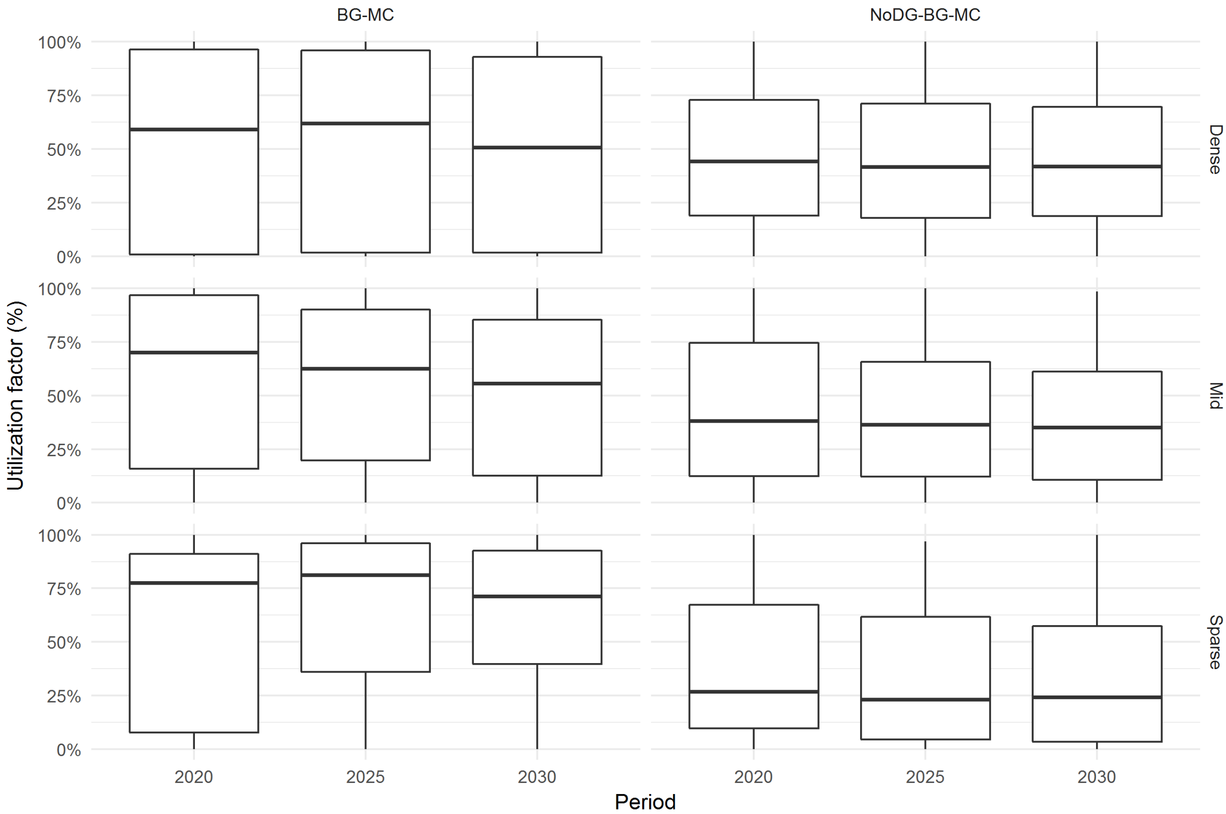

Fig. 5. ***LUF for least-cost scenarios with PV and storage (left) and without them (right).***

full portfolio of distributed resources are integrated into the grid. The northernmost nodes are now interconnected in a larger four-node minigrid system. By 2030, PV is installed on a few grid-connected nodes and all nodes, but the small minigrids are connected to the central grid.

D. Adoption of DER Increases Distribution System Efficiency Through Capital Deferments

Grid topology for systems that evolve based on distributed resources is very different than from a traditional system. To measure this, we compare the LUF between the "traditional" expansion scenario and the one where distributed resources are allowed. We find that grids with distributed resources are remarkably more efficient than grids without these resources, particularly in low-density areas (see Fig. 5). Median LUF for low-density systems with PV and storage is ~80% compared with ~25% in traditional systems. This is due to the shorter and reduced capacity networks and higher reliance on off-grid systems. Median LUF in high-density areas is about 10% higher when distributed PV and storage are allowed compared with the traditional expansion. Higher utilization factors generally translate to more efficient use of capital, which is critical in SSA countries that suffer from capital scarcity [48].

E. Relevant Tradeoff Between Transmission Expansion and Distributed Resource Deployment

Transmission expansion is substantially affected by the deployment of distributed resources, since the latter replace utility-scale generation that uses the transmission to reach load centers. In the "traditional" scenario, national-level transmission capacity is 140% larger than in the distributed resource scenario by 2020 and 84% larger by 2030. This reflects that distributed resources have important capital avoidance effects in the transmission system. The declining ratio—from 140% to 84%—responds to a faster increase in distribution circuit length and capacity in the scenario with distributed resources. These allocation decisions across the power system's value chain have relevant cost implications that we analyze later in this paper.

The generation capacity expansion decisions for the models without modular PV or storage are very different when compared to scenarios that include these technologies (see Fig. A7 in the supplementary material). Utility-scale generation installed capacity reaches about 12 GW by 2030 and decentralized generation about 4 GW by 2030. In the scenario with distributed PV and storage, decentralized capacity reaches over 17 GW by 2030, 60% in PV and 35% in storage. Utility-scale mix is unchanged, but installed capacity decreases to 9 GW by 2030. There is 10–15 times more distributed storage installed than utility-scale centralized storage. We test the effect of the system losses' parameter on this ratio in Section VI.

F. System That Integrates DER and Grid Extensions Is More Cost-Effective Than One That Does Not

The average cost of power or LCOE for the "traditional" expansion is 140 \$/MWh across the simulation period. Costs include annualized investment, fuel, other variable and fixed costs, and maintenance expenditures for generation, transmission, distribution, and distributed resources. The share of costs for centralized generation is 25%, for decentralized generation is 45% (almost all fuel costs), and for the distribution grid is 24% (see Fig. A5 in the supplementary material). The inclusion of modular PV and storage substantially reduces the average system LCOE to 103 \$/MWh across the simulation period. The assumptions are a DER PV cost of 2.3 \$/kW and 1.9 \$/kW and a DER storage cost of 460 \$/kWh and 300 \$/kWh in 2020 and 2030, respectively. Costs are 23% lower in the first period and 29% lower in the last period, driven by expected lower capital costs for both modular technologies. Installed capacity for distributed diesel falls from 4 to 1 GW in 2030 when PV and storage are available. The capacity factor of distributed diesel decreases from 40% to 29% with PV and storage, which is consistent with fuel savings by using capacity only in peak hours. The power system cost structure changes with the addition of modular PV and storage. There is an important shift from fuel expenditures to capital cost expenditure in the distribution sector, as PV and storage replace diesel generation. In this new scenario, 37% of system costs are capital investment in distributed resources and about 20% of system costs are capital investment in the distribution grid. There is a ~20% reduction in utility-scale generation investment and a ~40% reduction in distribution grid investment. Only 13% of system costs are variable, compared to almost 50% in the "traditional" scenario. Overall, distributed diesel expenditure decreases from \$39 billion to \$7 billion through the simulation horizon, an 85% reduction.

VI. SENSITIVITY ANALYSIS

GAP model results may be sensitive to several parameters and assumptions. Through our analysis, we identify four key assumptions that we test: distribution system losses' parameter, distribution grid extension costs, battery storage lifetime, and distributed storage and PV capital costs.

A. Losses (Distribution System Efficiency)

GAP model represents losses through an efficiency parameter set at 15% loss per 100 mi of distribution line instead of resistive and reactive line losses. The model then implements a transportation model instead of a power flow due to computational constraints. Technical and nontechnical distribution system losses are very high in SSA, reaching up to 50% in some cases [57]. It is important then to test the impact of distribution system's loss reduction in the expansion and operation of the whole value chain.

We test three alternative parameters at 3%, 5%, and 10% losses per 100 mi of distribution line over the system that allows distributed PV and storage (see Fig. A9 in the supplementary material). The loss parameter does not impact utility-scale generation installation, but it does impact distributed resource deployment. About 11 GW of distributed resources are installed by 2030 with the 3% parameter, increasing to over 15 GW with the original 15% parameter. This result is intuitive: as the grid is less efficient, larger deployment of distributed resources to meet demand at the node level becomes more cost-effective. Losses' levels have an effect on the optimal supply mode decisions and the threshold distances for transitioning into different supply modes (see Fig. A10 in the supplementary material). A detailed account of the losses' sensitivity analysis is included in the supplementary material.

B. Distribution Grid Extension Costs

Distribution grid extension costs vary considerably across regions within a country. The reference cost of 35 k\$/MW-km used in the GAP model comes from actual rural electrification projects developed in Kenya in the 2008–2010 period. However, costs may be lower in denser or more central areas, or they may decrease in time with learning rates. Treating the 35 k\$/MW-km as an upper threshold, we test three lower grid extension costs that we apply to the whole region: 2, 10, and 20 k\$/MW-km.

We first study the impact of grid extension in the supply mode. We hypothesize that there may be a substitution effect between grid extensions and distributed resource deployment. The results show that for high-density areas, the grid extension cost has little to no effect in the supply mode (see Fig. A12 in the supplementary material). Grid-connected nodes with distributed storage are the predominant supply mode for high-density nodes. At very low extension costs, medium-density area supply mode is similar to high-density areas. However, as extension costs increase, there are more nodes with grid-connected distributed PV and diesel.

The grid extension cost threshold that defines on- and off-grid nodes seems to be highly nonsmooth. Even at 20 k\$/MW-km, there are less than 3% off-grid nodes in medium-density areas compared with over 25% in the 35-k\$/MW-km scenario. This suggests the existence of a tipping point in that cost range. In contrast, there is a base level of 25% of off-grid nodes in low-density areas, regardless of extension cost levels. This suggests that electrification decisions in medium-density zones are more sensitive to expansion costs, but the off-grid supply in sparse areas depends mostly on topology and not on the economics of grid extensions.

Lower extension costs lead to reduced adoption of distributed resources and increased installation of utility-scale resources, including transmission capacity. We estimate an increased adoption of 0.5%–0.8% of utility-scale resources for each 1000 \$/MW-km reduction in grid extension costs. At the utility scale, lower distribution grid extension costs have a disproportionate impact on wind resource adoption compared to geothermal, storage, natural gas, and diesel technologies. There is 75% more wind capacity in the 2-k\$/MW-km scenario compared to the original 35 k\$/MW-km. This is due to wind cost-effectiveness but also to higher demand levels and diversity at the transmission level that facilitate wind integration. At the distributed scale, lower extension costs lead to significant reductions in solar PV and diesel but moderate reductions in distributed storage. This is due to the higher flexibility of storage to be used in grid-connected and off-grid applications, particularly in the Kenya system with a large presence of a low-cost baseload resource such as geothermal energy.

C. Battery Storage Lifetime

Chemical storage capacity can degrade relatively quickly under high cycling patterns, especially when used for ancillary services [58]. We cannot make lifetime of the battery depend on its operation in a linear model such as GAP, but we can test the impact of a shorter battery lifespan in the economics of this technology. We run a scenario with a three-year lifetime (instead of the original 15 years) based on anecdotal evidence that this would be the minimum lifetime of intensely cycled battery systems.

Battery storage useful life reduction leads to an increase in the relative costs of this technology compared with other alternatives. Total system costs are $\sim$12% higher with lower distributed storage useful life. Cost increase is driven by higher adoption and dispatch of distributed diesel generation, which in turn responds to reduced storage capacity, especially in medium- and low-density areas. As distributed storage is relatively more expensive, about 50% less storage capacity is installed in 2020 compared with the original scenario. Distributed PV capacity also decreases by the same ratio, which reflects the interdependence of these technologies. GAP compensates the reduction in storage capacity and PV production with increased diesel generation at the node level, plus 5%–10% increments in capacity at the utility-scale level.

D. Capital Cost Reductions for Distributed Resources

We want to test under what capital cost regimes the system will turn mostly to off-grid supply modes instead of grid-connected modes. We simulate a fictional scenario with a capital cost for PV and storage of 1000 original values and find that every single node is supplied with a combination of distributed PV and storage. This extreme and fictional simulation does confirm that the model would eventually make a pure off-grid supply choice, given low enough values.

We define a set of plausible alternative capital cost reduction pathways for distributed PV and storage. We employ the most optimistic cost reduction pathways in our source data [59], [60]. The original 2030 distributed PV cost is 1.9 \$/W and the new cost is 1 \$/W. The original 2030 distributed battery storage cost is 112 \$/kWh and the new cost is 90 \$/kWh. We find that these lower capital costs do not lead to more off-grid nodes but to more hybrid grid-connected nodes that now include PV and diesel. The share of off-grid nodes stays around 25%–30% similar to the share with the original capital costs.

We do find that the size of the distributed PV systems installed and the energy produced by them changes substantially with these lower costs. The national-level energy balance shows that about 50% of electricity is sourced from distributed PV by 2030 in a scenario with low PV and storage costs compared with 25% in the original scenario (see Fig. A13 in the supplementary material). We estimate the median node installed capacity for each distributed technology. We find that in low-density areas, the median storage and the PV system size barely change in the new scenario with lower capital costs. However, in medium- and high-density areas, the median PV system size increases from 33 to 42 and 12 to 20 MW by 2030, respectively (see Fig. A14 in the supplementary material). Interestingly, median distributed energy storage capacity decreases from 6.5 to 4 h in dense areas when capital costs are lower. This is possibly explained by PV capacity costs declining relatively faster than storage costs (50% compared with 25%). It follows that the optimal decision is to allocate capital for larger PV systems and store fewer hours of PV production in the middle of the day rather than longer hours of grid power at night. Then, the distribution system dispatch in denser areas with low DER costs mimics the low-density areas' dispatch patterns described earlier.

E. Financing Rates

Higher financing costs for the electricity sector in most emerging economies are explained largely by the risk and uncertainty involved in the planning, investment, and operation of these markets. This is particularly true for DER, because these technologies are relatively young and their business cases and applications are still immature and untested. In addition, most small residential DER systems are sold directly to end users whose creditworthiness is very hard to assess, which translates into higher financing rate premiums [61].

We test the impact of a very low (1%) and a very high (15%) financing rate for DER compared with the standard 7% used throughout this paper. The lower rate would reflect active intervention from the government to reduce financing rates by providing guarantees to lenders and developers or, alternatively, direct subsidies to investors. The higher rate better reflects the current reality of many individual users that are poor credit subjects and pay hefty premiums.

A very low financing rate makes the capital cost cheaper, which leads to an increase from 15 to 25 GW of DER capacity by 2030 compared to the base scenario (see Fig. A12 in the supplementary material). About 80% of this growth is in distributed solar, and the remaining is in distributed storage. In contrast, a very high finance rate causes a decrease in DER adoption to about 10 GW by 2030, again mostly in solar PV. The reduced DER capacity is partly offset by distributed diesel generation that becomes comparatively cheaper and minimal increase in centralized generation. The large capacity increase in DER adoption with a lower financing rate is reflected as well in energy consumption. With a low finance rate, about 35% of energy is supplied from DER, while in the base case, this share is about 20%. This suggests that even if financing rates were very favorable to DER, the central grid would still supply about two-thirds of the electricity consumed by customers in the system. Higher finance rates for DER also translate to an increase of ~15 $/MWh in average system costs by 2030, while lower rates reduce average system costs by a similar amount.

VII. DISCUSSION

One of the most robust results in this paper is the predominance of hybrid supply modes—nodes that are supplied electricity by a combination of grid power and DER—when modular storage and PV resources are available. In general, the share of grid-only nodes is close to zero for all scenarios where DERs are available, regardless of the value of any of the key variables analyzed in the sensitivity runs. The most prevalent hybrid supply modes are characterized by grid-connected distributed storage. In fact, across all scenarios analyzed, distributed storage is deployed in 70%–90% of the nodes. These results suggest that DERs enable the development of different distribution systems compared with the traditional design paradigms and that utilities should design their systems, including DER deployment from the onset. The actual decision point is not whether to supply a given node from centralized or decentralized resources, but the relative balance of the capacity of centralized and decentralized modes of supply, including the distribution and transmission grids.

The main supply mode commonly includes central grid operating jointly with storage and/or PV systems. Policy makers and utilities should consider that the joint deployment and operation of these three resources is more efficient than their individual deployment. This has an impact on the design of adoption targets that are focused on a single resource, such as the California storage mandate or rooftop PV adoption targets. Our results suggest that policies should focus on fostering hybrid systems in denser and higher consumption areas, and off-grid multiresource systems—diesel, storage, and PV—in specific sparser locations. The results also show how relevant it is to design these systems to be grid ready. Analyzing the sequencing of deployment in low-density areas suggests that nodes can be initially supplied in off-grid modes but later connected to an expanding distribution grid. This strategy may also have a relevant impact to accelerate electricity access in countries with a high number of unconnected households. Sequencing of DER and grid extension supply modes shows that distributed resource expansion is integral to meet load with high-reliability levels.

We find that including existing transmission and generation assets in the simulation made no difference in the electrification pathways. This suggests that sunk costs from the existing infrastructure have little to no influence on the evolution of undeveloped power systems. It follows that new investments will shape the future power systems in these regions. Another important consequence is that data for the existing transmission and generation assets may not be critical to develop electrification pathways. This is important for developing and calibrating bottom–up models, such as GAP that requires a large amount of data and that can benefit from an understanding of what data are more relevant. However, whether this conclusion applies to the distribution system is outside the scope of this paper, as data for this segment are not publicly available for testing.

The GAP model is unique in its ability to represent the whole value chain expansion, including generation and transmission. This may explain the relatively higher share of off-grid nodes of 25% across most scenarios compared with 10%–15% from the results in the previous studies. The share of off-grid nodes is relatively insensitive to most variables, including grid extensions, capital cost reductions, and financing costs, but it is sensitive to distribution system losses. As the distribution system operates more efficiently, with reduced losses, the share of off-grid nodes declines substantially. It is also notable that lower DER costs do not affect the share of off-grid nodes, but they do affect the installed DER capacity, especially in dense area nodes. Then, the design of strategies for universal access should not be contingent on potential declines in the costs of DER but relate to the performance of the distribution system.

The tradeoff between losses and number of off-grid nodes highlights a relevant design challenge. Utilities could invest in reducing distribution system losses by developing higher capacity systems and performing a more efficient commercial operation to reduce nontechnical losses. In doing this, utilities would be shifting investment from DER to the distribution grid infrastructure and utility internal processes. Alternatively, utilities could operate higher losses' systems by investing more in DER to reduce the cost-effectiveness of lost power. This decision will depend on how expensive it actually is to reduce technical and nontechnical losses. A reduction in loss parameter from 15% to 3% per 100 mi translates into a 12 $/MWh decrease in average system costs of. This is equivalent to approximately 1 $/MWh per % reduction. If the cost of reducing technical and nontechnical losses is above this value, it may be more beneficial to deploy more DER instead of expanding the distribution grid.

The inclusion of DER has important capital deferment consequences along the value chain, but particularly in the distribution system. We find about 40% of cost reduction in the distribution grid when DERs are available compared to when DERs are not available. This reduction in costs comes from decreased distribution link capacity, which is explained by links being sized to transport baseload demand rather than peak demand. Peak demand is met by integrating grid power with a combination of PV, storage, and diesel generation sourced at the node level. This result suggests that undeveloped systems should actively integrate DER, demand response, and other mechanisms into their design process to avoid overbuilding the distribution grid. In addition to capital and maintenance savings in distribution systems, the deployment of distributed resources may have relevant reliability consequences. For example, a higher number of circuits located in sparse areas can lead to less reliable systems with more failure points and longer interruptions (contingent to the reliability of the distributed resources). This is because a system with shorter and more concentrated circuits in sparse areas will be maintained at lower costs and may be recovered faster when outages occur. In denser areas, more meshed systems may be more resilient and redundancy may improve reliability parameters [62]. A power system with high penetration of DER has comparatively lower variable cost and higher fixed costs than a system that has low penetration of these resources. This new cost structure can have relevant consequences. First, it decouples power system economics from the volatile price swings of fossil fuels, particularly diesel. Reduced dependence on distributed diesel generation will improve reliability due to a decreased chance of fuel shortages that commonly affect remote areas. Second, larger capital expenditures will require much more active and novel financing mechanisms to attract enough capital and to assess the new types of risks that correlate with DER investments. Third, these findings highlight the relevance of ownership decisions for distributed resources, as their optimal deployment may reallocate significant capital away from the traditional utility that should these assets be owned by private actors. Finally, a capital intensive cost structure raises questions about the continued application of volumetric rates when almost 90% of power system costs are fixed.[5]

Financing mechanisms will have an important impact on the ability of utilities, regulators, and governments of developing high DER penetration power systems. Our findings comparing very low and very high financing rates for DER suggest that for every percent point increase from the standard financing rate, there is roughly 6% less DER capacity deployed and a 2% increase in system costs. Financing costs for DER have a direct impact on distribution system capacity sizing, as a system with lower financing costs and more DER deployment requires half the capacity in distribution links compared to a system with higher financing costs. Lowering financing costs does not only reduce prices but could lead to the development of a type of distribution system much more intensive in DER and very different from the "traditional" expansion pathway.

The deployment of storage reflects that its main purpose is to provide flexibility to the grid and to maximize the efficiency or utilization of the distribution lines. The number of nodes with storage increase as distribution losses is reduced, which reflects that storage becomes more valuable as its charging from the grid becomes less expensive due to higher distribution system efficiency. This finding would support the development of policies that encourage centrally dispatched distributed storage adoption. The GAP model cannot simulate the effect of storage if it was managed by each individual node or user, but the dispatch patterns suggest that there may be system-level benefits to a centralized management of storage asset dispatch.

Supply modes are relevant to understand grid design, but the DER capacity choice better characterizes grid operation and highlights a few of the critical features implicit in the GAP model. The size of storage increases substantially as load zones get denser, because storage is charged mostly from the grid and used to meet resource adequacy requirements. This result is possibly contingent on the fact that GAP makes centrally optimized dispatch decisions for distributed storage to achieve system-level least-cost operation. In most existing applications, behind the meter storage is managed by the owner to maximize their benefits subject to opportunities offered by net metering, net billing, or other policies. The widespread application of distributed storage in GAP may importantly depend on the ability of future distribution system operators (DSOs) to dispatch storage units located in their systems. In addition, node-level investment and operational decisions in the GAP model depend on the availability of locational marginal prices (LMPs) at the distribution level.

Until recently, the integrative planning approach of the GAP model had no comparable regulatory process. In most jurisdictions, integrated resource planning (IRP) covers generation and transmission alone, with distribution planning being an independent process [50]. However, in recent years, distribution planning has evolved to actively integrate DER, and IRP in some United States is requiring treatment of DER equivalent to supply-side resources [63]. These changes are being driven by the cost, resilience, reliability, and flexibility benefits brought by DERs and may benefit from the coordination and high-level perspective from a model such as GAP. In particular, the resilience benefits of DER may be substantial, but research is needed to produce resilience valuation frameworks useful for regulators [64].

[5]This result is relevant for Kenya, given the high volumes of geothermal and wind power that composes the optimal central system expansion. However, it is expected that power systems around the globe will transition to be supplied by technologies with low or zero variable cost to meet decarbonization targets.

Finally, expansion pathways generally do not change much between periods; 2020 investment choices do differ substantially across scenarios, but they do not change significantly for 2025 or 2030 for the same scenario. This may be driven in part by the lack of dynamism in most variables, with the exception of DER capital costs that decline during the simulation period. Including cost reductions over time for grid extensions or improvements over time in system efficiency could produce a higher temporal variation. As shown, these results suggest that electrification pathways are largely defined early in the investment periods and that there may be benefits to earlier and more aggressive action to develop systems that are heavily based in DER and that use hybrid supply modes. Starting with a "traditional" expansion with the expectation to transform the system later to adopt DER may be an expensive route with a high risk of unused legacy distribution system assets. ■

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