A MULTI-CRITERIA, LONG TERM ENERGY PLANNING OPTIMISATION MODEL CONSIDERING INTEGRATED ON-GRID AND OFF-GRID ELECTRIFICATION – THE CASE OF UGANDA

PUBLISHED IN APPLIED ENERGY 243 (2019): 288-312.

Philipp A. Trotter[a,b,1], Nathanial J. Cooper[c], Peter R. Wilson[d]

[a] Smith School of Enterprise and the Environment, University of Oxford, South Parks Road, Oxford OX1 3QY, UK.
[b] Department of Mechanical Engineering, University of Bath, Claverton Down, Bath BA2 7AY, UK.
[c] Department of Chemical Engineering, Imperial College London, Exhibition Road SW7 2AZ UK.
[d] Department of Electronic and Electrical Engineering, University of Bath, Claverton Down, Bath BA2 7AY, UK.

ABSTRACT Although electricity access is lowest in developing countries, the academic literature on generation expansion planning (GEP) has been informed almost exclusively by challenges in industrialised countries. This paper presents the first multi-objective, long-term energy planning optimisation model tailored towards national power systems with little existing power infrastructure. Location, type, capacity and timing of all generation and transmission additions are determined. Specifically, three novel generalisations of standard generation planning are introduced: (1) an expansion of the demand constraints to allow for industrial and household electrification rates below 100%, (2) a minimisation of sub-national electrification inequality in conjunction with minimising system costs considering environmental constraints, and (3) an integration of distribution infrastructure, explicitly including both on-grid and off-grid electrification. The model was successfully applied to the previously unexplored Ugandan national power system case. The results suggest that it is cost-optimal to maintain high sub-national electricity access inequality to meet Uganda's 80% electrification target in 2040. Yet due to high optimal shares of locationally flexible solar energy, equal access rates across all districts can be achieved by increasing discounted system cost by only 3%. This paper fundamentally challenges the Ugandan government's focus on nuclear energy and grid-based household electrification. Instead, it calls for solar concentrated power as a baseload option in the future and a focus on off-grid electrification which the model selects for the majority of household connections in 2040 even in a high-demand scenario.

Keywords: Long-term energy planning, multi-objective mixed integer linear programming, sub-Saharan Africa, generation expansion problem (GEP), on-grid versus off-grid electrification, Solar Concentrated Power.

[1] E-mail address: philipp.trotter@smithschool.ox.ac.uk.

TABLE OF CONTENT

NOMENCLATURE

Indices and sets	
$c \in C$	geospatial cells
$c_c \in C_c \subseteq C$	cells which are connected to the grid in baseline time t_0
$c_n \in C_n \subseteq C$	cells which are not connected to the grid in baseline time t_0
$c_{ec} \in C_{ec} \subseteq C$	cells which are crucial economic hubs for the country
$g \in G$	generation technologies
$l \in L$	transmission lines between two adjacent cells
$l_e \in L_e \subseteq L$	transmission lines between two adjacent cells which exist in baseline time t_0
$l_n \in L_n \subseteq L$	transmission lines between two adjacent cells which do not exist in baseline time t_0
$ld \in LD$	direction of flow along a transmission line (either from or to a specific cell)
$p \in P$	generation plants
$p_{off} \in P_{off} \subseteq P$	off-grid generation plants
$p_{on} \in P_{on} \subseteq P$	on-grid generation plants
$p_{nG} \in P_{nG} \subseteq P_{on}$	potential new on-grid plants located in any cell c_n
$p_{oS} \in P_{oS} \subseteq P_{on}$	on-grid solar PV and solar thermal plants
$p_I \in P_I \subseteq P_{on}$	on-grid plants where capacity can only be added once during the planning horizon
$p_{vol} \in P_{vol} \subseteq P_{on}$	on-grid plants with volatile electricity output (solar PV and wind)
$sp \in SP$	all (p_{nG},l_n) tuples where line l_n is part of the shortest path from p_{nG} to the grid
$t \in T = \{t_1, \dots, T\}$	planning times, ranging from the first planning time t_1 to final time T.
$t_t \in T_t \supset T$, $T_t = \{t_0, t_1, \dots, T\}$	total set of times, ranging from baseline time t_0 (status quo) to final time T.

Scalars

$CFTrans$	maximum capacity factor of transmission lines [%]
$CLkV$	conversion loss from increasing the voltage from distribution to transmission level [%]
$DOMSh$	annual distribution operation and maintenance cost share of investment [%]
ε_{urbRur}	minimum required degree of electrification equality between urban and rural areas [%]
ε_{reg}	minimum required degree of electrification equality between different sub-national cells [%]
k	Granularity step size for Pareto Front
$MaxLine$	maximum single transmission line capacity as share of total demand [%]
$MaxSol$	maximum cumulative size of solar plants in any cell c [MW]
$MaxVol$	maximum share of generation technologies with volatile electricity output [%]
$MinLine$	minimum transmission line capacity [MW]
$PDemRt$	historic ratio of peak power demand to annual electricity demand [MW/GWh]
RM	reserve margin as share of peak demand [%]
$TOMSh$	annual transmission operation and maintenance cost share of investment [%]

Parameters

CF_p	capacity factor of plant p
$CDisIR_{c,t}$	average per person investment cost for rural distribution infrastructure in cell c in time t [mn. USD p.c.]
$CDisIU_{c,t}$	average per person investment cost for urban distribution infrastructure in cell c in time t [mn. USD p.c.]
$CDisIROff_{c,t}$	average non-module investment cost for off-grid technologies in rural areas of cell c in time t [mn. USD/GWh]
$CDisIUOff_{c,t}$	average non-module investment cost for off-grid technologies in urban areas of cell c in time t [mn. USD/GWh]
$CGenI_{p,t}$	investment cost for plant p in time t [mn. USD/MW]
$CGenOM_{p,t}$	annual operation and maintenance cost for plant p in time t [mn. USD/GWh]
CO_2Em_p	Life cycle CO_2 emissions of each generation plant p [tons/GWh]
$CTrIDis_{l,t}$	fixed investment cost for transmission line l in time t [mn. USD]
$CTrIFix_{ln,t}$	fixed investment cost for previously non-existent transmission line l_n in time t [mn. USD]
$CTrIVar_{l,t}$	variable investment cost for transmission line l in time t [mn. USD/MW]
DF_t	discount factor in year t
$DemBus_{c,t}$	annual electricity demand of non-households (i.e. business) in cell c and time t [GWh]
$DemR_{c,t}$	annual electricity demand of rural households in cell c and time t [GWh]
$DemU_{c,t}$	annual electricity demand of urban households in cell c and time t [GWh]
$DLoss_l$	average loss of line l at distribution voltage [%]
$DLossBus_{c,t}$	average distribution losses to businesses in cell c and time t [%]
$DLossU_{c,t}$	average distribution losses to connect urban households in cell c and time t [%]
$DLossR_{c,t}$	average distribution losses to connect rural households in cell c and time t [%]
$EBIn_{l,ld,c}$	0-1 parameter, equals 1 if electricity flowing in direction ld along transmission line l enters cell c, and 0 otherwise
$EBOut_{l,ld,c}$	0-1 parameter, equals 1 if electricity flowing in direction ld along transmission line l exits cell c, and 0 otherwise
$ERTar_t$	electricity rate target for entire population in time t [%]
$ERTarBus_t$	electricity rate target for businesses in time t [%]
$ExBus_c$	existing electricity served to non-households (businesses) in cell c at baseline time t_0 [GWh]
$ExROff_c$	existing electricity served to rural households via off-grid technologies in cell c at baseline time t_0 [GWh]
$ExROn_c$	existing electricity served to rural households via the grid in cell c at baseline time t_0 [GWh]
$ExSup_p$	existing installed generation capacity of plant p at baseline time t_0 [MW]
$ExUOff_c$	existing electricity served to urban households via off-grid technologies in cell c at baseline time t_0 [GWh]
$ExUOn_c$	existing electricity served to urban households via the grid in cell c at baseline time t_0 [GWh]
$ExTr_l$	existing capacity of line l at baseline time t_0 at transmission voltage [MW]
$ExTrD_l$	0-1 parameter, equals 1 if the connection l between two adjacent cells is served through a existing line at distribution voltage at baseline time t_0
$GenEff_{p_{on}}$	generator efficiency for grid-connected plants p_{on} to transfer generated electricity to distribution voltage [%]
$MaxEm_t$	maximum allowed carbon emissions in time t [tons]
$MinErBus_t$	minimum demand which has to be met in crucial economic hubs [%]
$MinSize_{p_{on}}$	minimum required size of plant p_{on} [MW]
$PCM_{p,c}$	0-1 parameter matching plants to cells (i.e. equals 1 if plant p is in cell c, and 0 otherwise)
$PopR_{c,t}$	rural population in cell c in time t
$PopTot_t$	total population in time t
$PopU_{c,t}$	urban population in cell c in time t
$SPGrid_{p_{nG},l_n}$	0-1 parameter indicating the shortest path from a plant p_{nG} to the grid as it exists in baseline time t_0 (i.e. equals 1 if line l_n is part of the shortest path from plant p_{nG} to the grid, and 0 otherwise)
Sup_p	unexplored generation potential for generation plant p at baseline time t_0 [MW]
$TLoss_l$	average loss of line l at transmission voltage [%]

Continuous Variables	
$cTotDisI$	total discounted investment costs for distribution infrastructure [mn. USD]
$cTotDisOM$	total discounted operation and maintenance costs for distribution infrastrcture [mn. USD]
$cTotGenI$	total discounted investment costs for generation plants [mn. USD]
$cTotGenOM$	total discounted operation and maintenance costs for generation plants [mn. USD]
$cTotTrI$	total discounted investment costs for transmission lines [mn. USD]
$cTotTrOM$	total discounted operation and maintenance costs for transmission lines [mn. USD]
$disBus_{c,t}$	annual electricity sent to businesses in cell *c* in time *t* via distribution lines that connect adjacent cells [GWh]
$disR_{c,t}$	annual electricity sent to rural areas in cell *c* in time *t* via distribution lines that connect adjacent cells [GWh]
$disU_{c,t}$	annual electricity sent to urban areas in cell *c* in time *t* via distribution lines that connect adjacent cells [GWh]
$elBus_{c,t}$	electricity dedicated to businesses in cell *c* in time *t* [GWh]
$elUp_{c,t}$	electricity converted from distribution to transmission voltage in cell *c* in time *t* [GWh]
$elDown_{c,t}$	electricity converted from transmission to distribution voltage in cell *c* in time *t* [GWh]
$elROff_{c,t}$	off-grid electricity dedicated to rural households in cell *c* in time *t* [GWh]
$elROn_{c,t}$	on-grid electricity dedicated to rural households in cell *c* in time *t* [GWh]
$elUOff_{c,t}$	off-grid electricity dedicated to urban households in cell *c* in time *t* [GWh]
$elUOn_{c,t}$	on-grid electricity dedicated to urban households in cell *c* in time *t* [GWh]
$erBus_{c,t}$	electrification rate of businesses in cell *c* in time *t* [%]
$erR_{c,t}$	rural electrification rate of cell *c* in time *t* [%]
$erTot_{c,t}$	total electrification rate of cell *c* in time *t* [%]
$erU_{c,t}$	urban electrification rate of cell *c* in time *t* [%]
$gen_{p,t}$	annual electricity generation of plant *p* in time *t* [GWh]
$genCap_{p,t}$	newly installed generation capacity of plant *p* in time *t* [MW]
$genCC_{p,t}$	cumulative newly installed generation capacity of plant *p* in time *t* [MW]
$trans_{l,ld,t}$	annual electricity at transmission voltage sent along line *l* in direction *ld* in time *t* [GWh]
$transCap_{l,t}$	newly installed transmission capacity on line *l* in time *t* [MW]
$transCC_{l,t}$	cumulative newly installed transmission capacity on line *l* in time *t* [MW]
$transD_{l,ld,t}$	annual electricity at distribution voltage sent along line *l* in direction *ld* in time *t* [GWh]
Binary variables	
$xGen_{p_{on},t}$	1 if generation plant p_{on} is built in time *t*, and 0 otherwise
$xTrans_{l_n,t}$	1 if transmission line l_n is built in time *t*, and 0 otherwise

1. INTRODUCTION

The United Nations has defined universal access to electricity as one of its Sustainable Development Goals to be reached by 2030. Approximately 675 million people in sub-Saharan Africa (SSA) live without access to electricity, equating to more than half of all un-electrified people globally [1]. As most research on energy planning optimisation has been conducted in and applied to countries with well-developed power infrastructure, there is an alarming paucity of approaches designed for developing countries with low initial electrification rates. A recent review failed to identify any such long-term energy planning optimisation research applied to a case in SSA [2], as the objectives and challenges of a multifold national electrification rate increase differ markedly from planning objectives in developed countries.

1.1 Long-term national-level energy planning optimisation background

A suitable formulation of the long-term Generation Expansion Planning (GEP) problem is required to assist decision makers in designing cost-efficient energy system [3]. A solution to the problem yields the optimal type and size, location, as well as construction timing for new generation capacity over a long planning horizon to satisfy an expected energy demand. A planning horizon can be considered to be long-term if it spans 15 years or more [4].

Several review studies have discussed methods and trends for generation expansion as well as transmission expansion planning. Zhu et al. [5] as well as, more recently, Koltsaklis and Dagoumas [6] analyse the GEP literature, Latorre et al. [7] as well as Lumbreras and Ramos [8] review the transmission planning problem, while Hemmati et al. [9] discuss various combined generation and transmission planning approaches. Mathematically, the complete long-term GEP problem is a Mixed Integer Nonlinear Programming (MINLP) problem with multiple decision criteria and uncertainties. MINLP formulations have been used by Yuan et al. [10], as well as by Hemmati et al. [11], with the latter incorporating energy storage and environmental factors into their GEP model. In addition, various metaheuristic methods have been proposed as powerful alternatives to classical optimisation methods to deal with non-linearities and non-convexities. These can arise when studying optimal operational conditions of power plants [12], associated components such as converters [13] or complex electricity demand forecasting [14]. Kaboli et al. provide an informative visual classification overview of such metaheuristics [15]. If transmission is addressed, further nonlinearities exist if Kirchoff's Second Law is explicitly modelled. For instance, Zhang et al. formulated a MINLP planning problem considering transmission infrastructure [16]. Rider et al.'s proposed MINLP approach for generation and transmission planning combined heuristics and interior point approaches to solve their nonlinear sub-problems [17].

However, especially in those cases where the GEP problem has been applied to long-term case studies, avoiding the considerable computational complexity associated with such non-linear methods has led to highly insightful results. Recent advances have focused on considerably broadening the scope and level of analysis of the long-term GEP problem [8], which in turn required different assumptions to simplify the model. The consequential diversification of the GEP literature has integrated such issues as various risk assessments, a variety of new decision criteria beyond pure economic optimality, operational power system aspects, the inclusion of interdependencies with other systems such as water supply, energy storage and security of supply, as well as policy design. This has improved the understanding of the GEP's multifacetted nature [6]. Associated simplified solution approaches have included mathematical optimisation techniques such as Linear Programming (LP), various decomposition approaches, Mixed Integer Linear Programming (MILP) as well as meta-heuristic approaches. For instance, in their long-term energy planning study, Thangavelu et al. used an LP formulation to incorporate security of supply concerns with an environmental objective of low emissions [18]. Guo et al. similarly used an LP formulation to study the effect of different operational time scales as part of the Chinese power system under a cap-and-trade carbon scheme [19]. However, due to their potential to model binary investment decisions as well as fixed cost functions, MILP approaches have been a dominant method to expand the GEP problem. Pozo et al. proposed a three-level MILP model which integrates generation and transmission expansion planning [20]. Other scholars have used MILP models to account for reliability measures [21], different types of problem-inherent uncertainties [22] and scheduling decision making [23]. Meta heuristic approaches have frequently been argued to allow for a more comprehensive study of long-term energy planning [24]. Proposed algorithms include the hybrid Genetic Algorithms (GA) / dynamic programming approach developed by Park et al. [25], the adaptive Simulated Annealing (SA) algorithm proposed by Yildirim et al. [26], and Particle Swarm Optimisation (PSO) based algorithms [24], which have also been successfully used for transmission planning [27]. Some models were specifically designed to handle uncertainties through approaches such as stochastic programming [28] or interval-parameter linear programming [29].

This paper focuses on the subset of problems which related to national-level expansion planning. While some studies, such as Chen et al.'s work on China [30], do not divide their national power system into distinct cells, a number of recent works have done so.to study sub-national implications of their planning models. For example, Guo et al. in their long-term energy planning study of the Chinese power system deployed a linear levelised cost approach for their objective function, dividing the Chinese system into ten geographic cells [19]. Guerra et al. integrated generation and transmission capacity planning in their MILP formulation applied to the Colombian power system, which they divided into five sub-national cells [31]. Georgiou formulated an MILP model to solve the long-term energy planning problem for the Greek national electricity system [32]. The author similarly modelled the system using five different geographic cells and studied optimal transmission requirements between these cells. Sharan and Balasubramanian presented a single-period MILP model which includes power and fuel transportation costs and apply it to the case of Southern India, modelled via 48 demand nodes [33]. These last three works argue for the benefits of simultaneously optimising generation and transmission infrastructure. In general, the GEP problem can be formulated as either driven by a centralised monopoly-utility or by a deregulated market with several market participants [23].

The different types of decision criteria associated with generation and transmission planning imply that multi-objective models are well-suited for energy planning [8], an assertion which has been similarly made in the context of different market designs [34] and for renewable energy integration [35]. To be able to obtain solutions for a long-term national-level planning problem with reasonably high geographic resolution or multiple periods, multi-objective expansion planning using classical optimisation techniques has been dominated by assumptions which allow for linear methods. Ren et al. formulate a Multi-Objective Linear Programming (MO-LP) model for the planning of distributed energy systems and their environmental impact [36], while Luz et al. [37] as well as Zhang et al. [35] use MO-LP formulations to plan systems with high renewable energy penetration. Among the most prominent approaches for this type of problem are Multi-Objective Mixed Integer Linear Programming (MO-MILP) methods [38]. For instance, Muis et al. use a MO-MILP formulation to assess renewable energy integration in the presence of a carbon emission reduction target [39]. Antunes et al. similarly use a MO-MILP formulation for their environmentally informed GEP model instance [40]. In terms of the types of optimisation criteria studied, previous multi-objective approaches have most commonly considered the trade-off between costs and environmental impact. For instance, Koltsaklis et al., in their spatial MO-MILP energy planning model applied to the Greek system, included an environmental constraint in terms of carbon emissions, and solved their problem for different levels of maximum-allowed emission levels, effectively yielding non-dominated solutions in the cost-versus-emissions space [4]. In addition to minimising costs and environmental impact, Meza et al. modelled minimum imported fuel and energy price risks objectives [41, 42], Unsihuay-Vila et al. considered a technical objective of diversifying the generation mix as part of their MO-MILP model [43], Luz et al. maximised generation at peak load [37], while Trotter et al. minimised different political risk factors of the Southern African Power Pool [44] and a continental African case [45].

Different methods exist for solving multi-objective optimisation problems [46]. In the context of the GEP, popular approaches have included weighted sum methods (see [43] as well as [42]), compromise programming based on minimising the Chebyshev distance between the multi-objective solution and the (infeasible) ideal solution of the single-objective cases (see for instance [36] and [38], different variations of the ε-Constraint method (see for instance [35] and

[37]) where all but one of the objectives are introduced as constraints, and Fuzzy Decision Theory [47].

1.2 Long-term energy planning in developing countries with low electrification rates: problem characteristics and literature gaps

Applying the long-term GEP to developing countries alters the problem in several fundamental ways when compared to its conventional formulation. This is due to the fact that in many developing countries, electricity access rates are considerably below 100%. In sub-Saharan Africa, the average access rate is below 40%. In Uganda, it is roughly 20% [48]. It is crucial to have robust planning methods in place for sub-Saharan Africa which cover the next two decades in order to efficiently overcome the energy access challenges there [49]. Specifically, three crucial aspects which characterise the long-term energy planning problem in developing countries have not yet been addressed in the mainstream GEP literature. Namely, these are (1) the presence of substantial planned suppressed demand due to insufficient initial power infrastructure, (2) the challenge of dealing with highly unequal access to electricity on a sub-national level, and (3) the importance of integrating on-grid and off-grid electrification options into an expansion planning optimisation model. The following paragraphs explain these three issues and the literature gaps associated with them in turn, while section 1.3 explains this paper's novel contributions to the literature by specifically addressing these three gaps.

First, while demand for electricity exists throughout a given developing country, the power infrastructure may only cover small parts of the country. SSA is home to 18 of the 19 countries worldwide which have reported an electrification rate of below 30% in 2016 [1]. Hence, a static constraint to meet all demand in a country which is the way the long-term energy planning problem has commonly been formulated in the literature is not a sensible modelling approach in a developing country context. Rather, most African governments have set electrification rate targets below 100% for the next one to two decades. To assist the associated infrastructure expansion decision-making process, a long-term national-level planning model needs to model demand as meeting this electrification rate target throughout the planning horizon, hence allowing for planned suppressed demand.

Second, electricity access is distributed in highly unequal ways throughout SSA [50]. While it is accepted that such social implications have often been fundamental to whether or not electrification in developing countries has succeeded or not [2], to the best of our knowledge, they have not yet been explicitly modelled in long-term national-level generation and transmission planning optimisation models. Lumbreras and Ramos in their review article note that social acceptance of new transmission corridors is an important optimisation objective in transmission expansion planning, but do not identify works which have modelled it explicitly [8]. A few energy-related multi-objective optimisation studies, however, have demonstrated their relevance in SSA. For instance, Pérez-Fortes et al. in their MO-MILP model of biomass energy systems in specific small areas in Ghana used the maximisation of job creation across communities as one of their objectives [51]. Arndt et al. included a measure for employment reduction to socially evaluate different decarbonisation strategies of South Africa's energy sector [52]. Beck et al. included a social score based on the potential to contribute to rural electrification and evaluated a bio-energy network in the Kwazulu Natal region in South Africa [53]. The issue of sub-national electrification inequality, however, has not yet been modelled as an objective. SSA is the only major world region where there is a more than threefold gap between rural and urban electrification (Figure 1, see also [50]). Similar inequalities exist for different sub-national regions of the same country. As a consequence, electrification has turned into a political good in SSA: Incumbents have frequently promised to provide access to their political supporters during electoral campaigns (see [54] and more recently [45]). Decision makers are thus faced with the challenge of electricity access being a deeply socio-political issue, and energy planning efforts would do well to consider such dimensions.

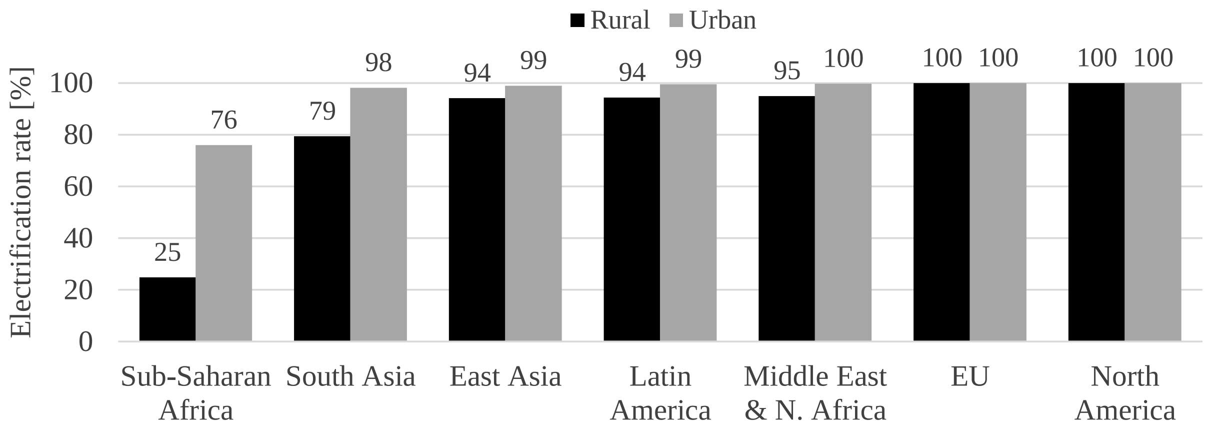


Figure 1: Rural and urban electrification in major world regions in 2016 (data source: [1])

Third, while the traditional GEP focuses on generation expansion, expanded by some scholars to transmission planning [9], the low number of connections in many African countries warrants the inclusion of distribution planning. This is necessary to capture where exactly new connections are provided, which in turn yields the actual, non-suppressed demand the network needs to meet. What is more, in addition to the traditional on-grid focus of the GEP, off-grid solutions have been found to be cheap electrification alternatives in many African countries and thus need to be part of an integrated planning approach, at least as a bridge technology to achieve widespread electrification in the next decades [55]. Several planning studies have used geographic information system (GIS) software to determine the cost-optimal mode of electrification in developing countries. Cases include village-level studies [56], country-level assessments in Kenya [57], Burkina Faso [58] and Senegal [59] as well as on a continental African scale for rural [60] and for all households [61]. These GIS-based studies proposed different approximations to calculate the costs of different electrification alternatives for a certain spatial area and then choose the cheapest alternative per spatial area. Interactions between each of these spatial areas are limited or non-existent in most of these studies. Mentis et al.'s work is notable for their continental scale, the quality of their GIS data and their usage of small spatial units of 1 km^2 [61]. They found a high penetration of standalone technologies as part of the preferred power system, especially for low per capita demand scenarios. Other scholars have used the pre-defined cost-minimisation planning model of the Network Planner software to determine the least-cost choice between grid and off-grid electrification in African cases, namely for Nigeria [62] and Ghana [63]. However, while such approaches allow for choosing a high spatial resolution due to limited computational complexity, all these studies treat grid extension as a black box, attributing an assumed overall cost rather than explicitly modelling electricity flows, the implications for the optimal on-grid generation mix or respective generation plant locations and timing. These studies were also largely focused on household access to electricity and often not concerned with non-domestic demand which usually makes up around three quarters of overall demand.

1.3 Novelty of the presented model

This paper is the first to expand the long-term GEP such that it can readily be used for developing country cases with limited initial electricity infrastructure. It contributes to the trends of broadening the GEP problem and the usage of MO-MILP methods evident in the literature review in section 1.1. Specifically, this paper presents a novel long-term, spatially explicit, multi-period MO-MILP energy planning model, featuring the following three main novel generalisations, each addressing one of the three literature gaps identified in section 1.2.:

- The design and application of a national-level energy planning optimisation tailored towards developing countries with limited initial power infrastructure, imposing the demand-side constraint of meeting a given overall electrification rate target which can be set to any number between 0 and 100% at any time period. Hence, the model is able to choose to meet demand in some sub-national areas, and supress it in others. This constitutes a generalisation of the conventional generation and transmission expansion planning problem where demand has to be met at all nodes and times.

- The model defines sub-national electrification inequalities (both urban versus rural and regional access differences) as a separate optimisation criteria. The model's multi-objective approach yields the optimal trade-off between minimising system costs and different types of sub-national electrification inequalities expressed in a spatially explicit way, considering a significant number (> 100) of sufficiently small discrete geographic cells.
- In addition to integrated generation and transmission expansion planning, the model includes an aggregated formulation of distribution infrastructure to indicate where new connections are planned. Crucially, the model integrates both on-grid and off-grid electrification options to provide energy access, with the latter being projected to play an important part in electrifying developing countries. This integrated model is able to derive implications for the optimal split between off-grid and on-grid electrification of people without access, as well as derive the implicit load implications on the grid.

Furthermore, the model's application is novel as it constitutes the first energy optimisation study of any kind of the Ugandan network. As all data used is real-life data, the paper is able to compare its solutions with official Ugandan energy expansion policies and offer improvements over current plans.

The remainder of this paper is structured as follows. Section 2 presents the problem statement to describe the overall structure and key assumptions of the model. Section 3 mathematically defines the model, section 4 provides the solution approach. Section 5 briefly introduces the method used for modelling result validation while data requirements for the Ugandan case are briefly discussed in section 6. Section 7 presents the solution of the model and tests the least-cost network via an indicative load flow analysis, section 8 shows the significant differences between the model results and Uganda's official national energy plan. Finally, a conclusion is offered in section 9.

2. PROBLEM STATEMENT

The problem is stated in terms of the following factors and assumptions:

i. *Overall structure and objectives*: The MO-MILP model performs long-term energy planning by dividing the system into a number of distinct geographic cells *c* over multiple time periods *t*. It is tailored towards cases with low initial electrification rates, and minimises the discounted system costs, consisting of the investment as well as operation and maintenance cost of generation, transmission and distribution infrastructure. Furthermore, it includes objectives to minimise urban versus rural and regional electrification inequality within a country (or other unit of analysis).

ii. *Demand*: The model includes three kinds of demands, namely urban household, rural household and non-household (i.e. business and public sector) demand, each aggregated per cell *c* and time period *t*. Both an annual electricity demand (in GWh) and a peak load demand with a minimum capacity reserve margin (in MW) have to be met. In accordance with the decision problem commonly faced by planners, the main demand constraints are formulated in terms of meeting minimum national-level electrification rates. The model is thus free to choose which sub-national cells it electrifies (fully or partially) to meet these targets. To account for uncertainty in demand forecasts, different demand scenarios are considered.

iii. *Generation*: The available on-grid generation options *g* include both renewable energy sources (solar PV, solar concentrated power (CSP), wind, biomass, hydro and geothermal) as well as non-renewables (natural gas, coal, oil and nuclear). Furthermore, several off-grid generation options (solar PV with storage, mini-hydro and diesel) are considered, however they are limited to provide domestic demand only as industrial demand is assumed to require grid-connected electricity. Generation potentials for each technology are aggregated per geographic cell *c*, and together with their associated capacity factors depend on the endowments in each cell. While all on-grid plants must at least be of a specific positive minimum capacity size if built (binary decision variables required), any fractional installed capacity is allowed for off-grid technologies as they are readily scalable down to several Watts (no binary decision variables required). Generation resilience constraints include a maximum capacity percentage from volatile on-grid sources, a minimum reserve margin requirement at peak power demand and a minimum geographical spread of solar plants to balance weather fluctuations.

iv. *Carbon emissions*: The model limits annual carbon emissions from generation. In the specific country case of Uganda, the limit was set according to Uganda's intended contributions as part of the Paris Agreement.

v. *Transmission*: Each neighbouring cells c_1 and c_2 can be connected via a transmission line l. Each line l is assumed to connect the centroids of c_1 and c_2, and is assumed to be 20% longer than the straight-line distance between these centroids due to geographic barriers. A line l either exists in baseline time t_0 (if an existing transmission line connects c_1 and c_2), or can be built from scratch. The model allows for upgrading the capacity for existing lines. Distances between geographic cells are assumed to be large enough that constructing lines at distribution voltage (33 kV and below) between them is always sub-optimal to constructing transmission lines.[2] Furthermore, the model ensures that all new power plants to be built in unconnected cells are being connected to one continuously interconnected grid using a shortest path to the grid heuristic (see Appendix A).

vi. *Distribution*: The model includes existing distribution infrastructure between cells (mostly 33 kV), enabling the model to transmit electricity at low voltage. While such low-voltage are sub-optimal when compared to transmission lines, they nevertheless frequently exist in developing countries and covering considerable distances. The model furthermore considers distribution infrastructure within each cell to determine the optimal choice of an on-grid versus off-grid electrification strategy for households by calculating average urban and rural distribution costs per person. The different distribution line length requirements in urban and rural areas located in each cell c which are necessary to estimate the per person distribution costs follow from a simple tree-type network approximation (see van Ruijven et al. (2012) [64]) which mainly depends on average household size and density in urban and rural areas (see Appendix B). Within-cell distribution cost for businesses are neglected due to the considerably larger amount of household connections and their low variability between cells.

vii. *Market-type:* Generation and transmission planning is often done in a centralised way in developing countries, with a governmental body being responsible (similar to what Unsihuay-Vila et al. have argued for the Brazilian case [43]). The model thus assumes a simple monopoly-type market setting.

[2] For the cost data in the Ugandan case, the distance where constructing 132 kV transmission lines becomes cost-optimal vis-à-vis constructing 33 kV distribution lines over their lifetime is roughly 5 km. The minimum length of any potential transmission line in the 112 district Ugandan case example is 9 km.

3. MATHEMATICAL FORMULATION

This section presents the novel MO-MILP model laid out in section 2. First, the objective functions are discussed in section 3.1. The subsequent sections address the constraints surrounding demand (section 3.2), energy balances (section 3.3), generation and environmental impact (section 3.4), transmission (section 3.5), distribution (section 3.6) and network resilience (section 3.7). The solution approach, based on applying an ε-constraint method to the non-monetary objective functions, is detailed in section 4.

3.1 Objective functions

This model considers three different objective functions, namely (1) total discounted cost minimisation, (2) urban versus rural electrification inequality minimisation, and (3) regional electrification inequality minimisation. Objective function (1) sums the discounted generation, transmission and distribution investment costs, *cTotGenI*, *cTotTrI* and *cTotDisI*, respectively, as well as the discounted generation, transmission and distribution operation and maintenance (O&M) costs, *cTotGenOM, cTotTrO* and *cTotDisOM*. Expression (2) minimises the maximum discrepancy of urban electrification rate $erU_{c,t}$ versus rural electrification rate $erR_{c,t}$ in any geographic cell c at final planning time horizon period T. The maximum discrepancy of the total electrification rate $erTot_{c,t}$ between any two regions, i.e. cells $c_1, c_2 \in C$, in final period T is minimised in (3):

$$\min f_{cost} = cTotGenI + cTotGenOM + cTotTrI + cTotTrOM + cTotDisI + cTotDisOM \tag{1}$$

$$\min f_{urbrur} = \max_{c \in C}\left(\left|erU_{c,T} - erR_{c,T}\right|\right) \tag{2}$$

$$\min f_{reg} = \max_{c_1, c_2 \in C}\left(erTot_{c_1,T} - erTot_{c_2,T}\right) \tag{3}$$

3.1.1 Cost objective function

3.1.1.1 Generation investment and O&M costs

The total discounted investment costs of all newly installed generation capacity are calculated by summing the product of newly installed generation capacity $genCap_{p,t}$ and their associated costs $CGenI_{p,t}$ over all potential generation plants p and time periods t, multiplied by discount factor DF_t. Similarly, the total discounted O&M costs follow from summing the product of generated electricity $gen_{p,t}$ from the plant as well as time-specific O&M costs, $CGenOM_{p,t}$ as follows:

$$cTotGenI = \sum_t \left[DF_t \cdot \sum_p \left(genCap_{p,t} \cdot CGenI_{p,t} \right) \right] \tag{4}$$

$$cTotGenOM = \sum_t \left[DF_t \cdot \sum_p \left(gen_{p,t} \cdot CGenOM_{p,t} \right) \right] \tag{5}$$

3.1.1.2 Transmission investment and O&M costs

The fixed transmission investment costs $CTrIFix_{ln,t}$ are multiplied with binary decision variable $xTrans_{ln,t}$, a variable equal to 1 if previously non-existent transmission line l_n is built between two adjacent geographic cells in time t, and 0 otherwise. The variable investments costs $CTrIVar_{l,t}$ are multiplied with the newly added transmission line capacity $transCap_{l,t}$ on line l in time t. The O&M costs of transmission for lines at transmission voltage are calculated by assuming a fixed O&M cost share of investment, *TOMSh*, to occur every time t. Hence, *TOMSh* is multiplied with the installed capacity on line l (the sum of already existing capacity at baseline time period t_0, $ExTr_l$, and the cumulative newly added line capacity $transCC_{l,t}$ between t_1 and t) and the associated investment costs per line, $CTrIVar_{l,t}$. Furthermore, where distribution lines exist between cells in time t_0, i.e. where parameter $ExTrD_l$ is equal to 1, their maintenance cost is included in equation (7) via their O&M cost share of investment, *DOMSh*, multiplied by the original investment cost of the line, $CTrIDis_{l,t}$.

$$cTotTrI = \sum_t DF_t \cdot \left(\sum_{l_n} xTrans_{l_n,t} \cdot CTrIFix_{l_n,t} + \sum_l transCap_{l,t} \cdot CTrIVar_{l,t} \right) \tag{6}$$

$$cTotTrOM = \sum_t DF_t \cdot \sum_l \left(\left(transCC_{l,t} + ExTr_l \right) \cdot CTrIVar_{l,t} \cdot TOMSh + ExTrD_l \cdot CTrIDis_{l,t} \cdot DOMSh \right) \tag{7}$$

3.1.1.3 Distribution investment and O&M costs

Cost parameters $CDisIU_{c,t}$ and $CDisIR_{c,t}$ denote the average per-person investment cost for on-grid distribution infrastructure in urban areas and rural areas of cell c, respectively (see section 5 for details). The number of people with new access to electricity through the grid follows from multiplying urban and rural populations in each cell and time, $popU_{c,t}$ and $popR_{c,t}$, with the annual electricity distributed in cell c and time t, $elUOn_{c,t}$ in urban and $elROn_{c,t}$ in rural areas, lowered by distribution losses $DLossU_{c,t}$ and $DLossR_{c,t}$, and divided by the respective electricity demand $DemU_t$ and $DemR_t$ respectively. In addition, non-module investment costs of off-grid technologies are included (such as logistics costs to provide modules to remote households). They follow from multiplying the newly generated off-grid electricity in cell *c* time *t*, $elUOff_{c,t}$ – $elUOff_{c,t-1}$ for urban and $elROff_{c,t}$ – $elROff_{c,t-1}$ for rural areas, by an assumed non-module investment unit cost, $CDisIUOff_{c,t}$ and $CDisIUOff_{c,t}$. The consumed electricity in baseline period t_0 is known and modelled as an input parameter in accordance to the right-hand side of equations (9) – (12).

$$\begin{aligned} & cTotDisI \\ & = \sum_t DF_t \cdot \sum_c \Bigg(\left(\frac{elUOn_{c,t} \cdot (1 - DLossU_{c,t})}{DemU_t} \cdot popU_t - \frac{elUOn_{c,t-1} \cdot (1 - DLossU_{c,t-1})}{DemU_{t-1}} \cdot popU_{t-1} \right) \cdot CDisIU_{c,t} \\ & \qquad + \left(\frac{elROn_{c,t} \cdot (1 - DLossR_{c,t})}{DemR_t} \cdot popR_t - \frac{elROn_{c,t-1} \cdot (1 - DLossR_{c,t-1})}{DemR_{t-1}} \cdot popR_{t-1} \right) \cdot CDisIR_{c,t} \\ & \qquad + (elUOff_{c,t} - elUOff_{c,t-1}) \cdot CDisIUOff_{c,t} + (elROff_{c,t} - elROff_{c,t-1}) \cdot CDisIROff_{c,t} \Bigg) \end{aligned} \tag{8}$$

$$elUOn_{c,t_0} \cdot (1 - DLossU_{c,t_0}) = ExUOn_c \qquad \forall c \tag{9}$$

$$elROn_{c,t_0} \cdot (1 - DLossR_{c,t_0}) = ExROn_c \qquad \forall c \tag{10}$$

$$elUOff_{c,t_0} = ExUOff_c \qquad \forall c \tag{11}$$

$$elROff_{c,t_0} = ExROff_c \qquad \forall c \tag{12}$$

Analogously to (7), equation (13) multiplies the O&M cost share of investment *DOMSh* with the cumulative distribution investment until time period *t*, and then sums over all cells and planning time periods. All O&M costs for off-grid technologies are considered as part of the generation O&M costs and thus do not feature in (13).

$$\begin{aligned} cTotDisOM = & \sum_t DF_t \cdot DOMSh \\ & \cdot \sum_c \left(\frac{elUOn_{c,t} \cdot (1 - DLossU_{c,t})}{DemU_t} \cdot popU_t \cdot CDisIU_{c,t} + \frac{elROn_{c,t} \cdot (1 - DLossR_{c,t})}{DemR_t} \cdot popR_t \right. \\ & \left. \cdot CDisIR_{c,t} \right) \end{aligned} \tag{13}$$

3.1.2 Electrification inequality objective functions

The objective functions considering electrification inequalities are expressed in terms of annual rural, urban and total electrification rates. These follow from dividing the total distributed on-grid electricity, $elUOn_{c,t}$ for urban and $elROn_{c,t}$ for rural areas, as well as the associated off-grid electricity $elUOff_{c,t}$ and $elROff_{c,t}$ in cell c and time t, the former lowered by distribution losses $DLossU_{c,t}$ and $DLossR_{c,t}$, by the respective demands in cell c and time t, $DemU_{c,t}$ and $DemR_{c,t}$. The total electrification rate of a cell at a certain time is a population-weight sum of urban and rural electrification. The model furthermore includes an explicit upper bound on all electrification rates of 100.

$$erU_{c,t} = 100 \cdot \frac{elUOn_{c,t} \cdot \left(1 - DLossU_{c,t}\right) + elUOff_{c,t}}{DemU_{c,t}} \qquad \forall c,t \qquad (14)$$

$$erR_{c,t} = 100 \cdot \frac{elROn_{c,t} \cdot \left(1 - DLossR_{c,t}\right) + elROff_{c,t}}{DemR_{c,t}} \qquad \forall c,t \qquad (15)$$

$$erTot_{c,t} = \frac{erU_{c,t} \cdot popU_{c,t} + erR_{c,t} \cdot popR_{c,t}}{popU_{c,t} + popR_{c,t}} \qquad \forall c,t \qquad (16)$$

3.2 Demand constraints

3.2.1 Domestic demand

The model generalises the common demand constraint in GEP. It requires meeting an overall domestic electrification rate target $ERTar_t$ which is calculated as a population-weighted sum of individual cell urban and rural electrification rates (17). Where $ERTar_t = 100$, all demand would need to be met at all nodes and all times as is the case in conventional planning model formulations. However, as $ERTar_t < 100$ is usually the case for the coming decades in sub-Saharan African countries, the options of the model to meet demand rises exponentially with the cardinality of the set of cells $|C|$. Hence, this generalisation complicates the model as its degrees of freedom are considerably increased.

$$\frac{\sum_c erU_{c,t} \cdot popU_{c,t} + erR_{c,t} \cdot popR_{c,t}}{popTot_t} \geq ERTar_t \qquad \forall t \qquad (17)$$

Furthermore, all previously served demand in urban and rural areas through on and off-grid technologies in baseline time period t_0, $ExUOn_c$, $ExROn_c$, $ExUOff_c$, and $ExROff_c$ respectively, has to be met in subsequent time periods (considering average distribution losses within cell c in time t in urban and rural areas, $DLossU_{c,t}$ and $DLossR_{c,t}$,):

$$elUOn_{c,t} \cdot \left(1 - DLossU_{c,t}\right) \geq ExUOn_c \qquad \forall c,t \qquad (18)$$

$$elROn_{c,t} \cdot \left(1 - DLossR_{c,t}\right) \geq ExROn_c \qquad \forall c,t \qquad (19)$$

$$elUOff_{c,t} \geq ExUOff_c \qquad \forall c,t \qquad (20)$$

$$elROff_{c,t} \geq ExROff_c \qquad \forall c,t \qquad (21)$$

3.2.2 Business demand

Similarly, meeting business demand is modelled by requiring at least a certain overall fraction of total demand, $ERTarBus_t$, to be met in year t without specifying the geographical areas where this demand fraction should be met. Each rate $erBus_{c,t}$ follows from dividing $elBus_{c,t}$, lowered by distribution losses $DLossBus_{c,t}$, with the business demand. The overall business electrification rate is then calculated by weighing each cell's rate with its fraction of total business demand.

$$erBus_{c,t} = 100 \cdot \frac{elBus_{c,t} \cdot \left(1 - DLossBus_{c,t}\right)}{DemBus_{c,t}} \qquad \forall c,t \qquad (22)$$

$$\frac{\sum_c erBus_{c,t} \cdot demBus_{c,t}}{\sum_c demBus_{c,t}} \geq ERTarBus_t \qquad \forall t \qquad (23)$$

Furthermore, at least the business demand served in baseline time t_0 has to be met in all cells at all times:

$$elBus_{c,t} \cdot \left(1 - DLossBus_{c,t}\right) \geq ExBus_c \qquad \forall c,t \qquad (24)$$

3.2.3 Total peak demand

The total demand in GWh served through the grid is converted to peak power demand in MW by multiplying it with scalar *PDemRt* which denotes the historically observable ratio between peak power and annual electricity demand. Constraint (25) requires that the total on-grid installed capacity in each time t, modelled as the sum over all newly added and pre-existing grid-connected capacity, $genCC_{pon}$ and $ExSup_{pon}$, is greater than peak demand by at least the reserve margin *RM*.

$$\sum_{p_{on}} \left(ExSup_{p_{on}} + genCC_{p_{on},t}\right) \geq RM \cdot PDemRt \cdot \sum_{c} \left(elUOn_{c,t} \cdot \left(1 - DLossU_{c,t}\right) + elROn_{c,t} \cdot \left(1 - DLossR_{c,t}\right) + elBus_{c,t} \cdot \left(1 - DLossBus_{c,t}\right)\right) \quad \forall t \quad (25)$$

3.2.4 Socio-economically motivated demand

Any given electrification rate in each cell *c* must be at least sustained in two subsequent periods, as a reduction in domestic electrification rates in any district should be avoided. Moreover, constraint (27) considers the fact that certain districts c_{ec} may be fundamental economic hubs of a country where a specific, large share $MinErBus_t$ of business demand must be met. In Uganda, this is the case for the capital city Kampala which has a unique role both economically and politically.

$$erTot_{c,t} \geq erTot_{c,t-1} \quad \forall c, t \quad (26)$$

$$erBus_{c_{ec},t} \geq MinErBus_t \quad \forall c_{ec} \in C_{ec}, t \quad (27)$$

3.3 Energy balance constraints

3.3.1 Transmission voltage on-grid energy balance

For each cell *c*, electricity input must equal electricity output in each time period *t*. Each cell receives electricity via transmission $trans_{l,ld,t}$ if parameter $EBIn_{l,ld,c}$ equals 1, i.e. if transmitted electricity flowing along line *l* in direction *ld* enters cell *c*. Similarly, transmission leaves cell *c* where parameter $EBOut_{l,ld,c}$ equals 1. All incoming transmission is reduced by loss parameter $TLoss_l$. Furthermore, each cell may get electricity input at the transmission level if some electricity $elUp_{c,t}$ is generated in cell *c* and then converted upward to transmission voltage to be sent elsewhere. Alternatively, electricity transmitted from elsewhere may be converted down to distribution voltage, hence variable $elDown_{c,t}$ is included on the right-hand side of equation (28). Again, conversion losses *CLkV* are multiplied for electricity input.

$$\underbrace{\sum_{l} \sum_{ld} trans_{l,ld,t} \cdot EBIn_{l,ld,c} \cdot (1 - TLoss_l) + elUP_{c,t} \cdot (1 - CLkV)}_{in} = \underbrace{\sum_{l} \sum_{ld} trans_{l,ld,t} \cdot EBOut_{l,ld,c} + elDown_{c,t}}_{out} \quad \forall c, t \quad (28)$$

3.3.2 Distribution voltage on-grid energy balance

At the distribution voltage level, all generated electricity in a cell plus incoming electricity from other cells after losses must equal outflowing electricity plus electricity used for distribution within the cell to meet demand. Losses incurred to convert generated electricity $gen_{pon,t}$ from plant p_{on} to distribution voltage are captured through efficiency parameter $GenEff_{pon}$. Parameter $PCM_{pon,c}$ matches generation plants p_{on} to cells c by being equal to 1 if p_{on} is in c, and 0 otherwise. As intercell distribution lines may exist in time t_0, equation (29) contains terms of distribution $transD_{l,ld,t}$ which models electricity exchange at distribution level between cells, incurring a loss $DLoss_l > TLoss_l$. These terms are multiplied with parameter $ExTrD_l$, thereby limiting them to already existing lines in baseline time t_0. Electricity converted down from transmission to distribution voltage in cell c, $elDown_{c,t}$, is an input, while electricity converted upwards, $elUp_{c,t}$ is an output. Furthermore, variables $elBus_{c,t}$, $elUOn_{c,t}$ and $elROn_{c,t}$ denote the electricity used via the distribution grid within cell c in time t to serve business, urban and rural demand, respectively.

$$\underbrace{\sum_{p_{on}} gen_{p_{on},t} \cdot GenEff_{p_{on}} \cdot PCM_{p_{on},c} + \sum_{l}\sum_{ld} transd_{l,ld,t} \cdot EBIn_{l,ld,c} \cdot DLoss_l \cdot ExTrD_l + elDown_{c,t} \cdot (1 - CLkV)}_{in}$$
$$= \underbrace{\sum_{l}\sum_{ld} transD_{l,ld,t} \cdot EBOut_{l,ld,c} \cdot ExTrD_l + elUp_{c,t} + elBus_{c,t} + elUOn_{c,t} + elUOn_{c,t}}_{out} \quad \forall c, t \quad (29)$$

3.3.3 Off-grid energy balance

For off-grid generation technologies, the associated energy balance is simply that the sum of off-grid generation $gen_{poff,t}$ equals the electricity consumed from off-grid sources in urban and rural areas in each cell c and time t, $elUOff_{c,t}$ and $elROff_{c,t}$, respectively.

$$\underbrace{\sum_{p_{off}} gen_{p_{off},t} \cdot PCM_{p_{off},c}}_{in} = \underbrace{elUOff_{c,t} + elROff_{c,t}}_{out} \qquad \forall p, t \qquad (30)$$

3.4 Generation constraints

3.4.1 Generation supply potential

The cumulative newly added capacity of a plant p in t, $genCC_{p,t}$, is the sum of all newly added capacity in certain time period t, $genCap_{p,t}$, up until t (31). Note that $genCC_{p,t0} = 0$. The supply potential Sup_p for each plant is the upper bound for $genCap_{p,t}$, lowered in time $t > t_1$ by any capacity which may have been added planning periods prior to t (32).

$$genCC_{p,t} = \sum_{\tau=t_1}^{t} genCap_{p,\tau} \qquad \forall p, t \qquad (31)$$

$$genCap_{p,t} \leq Sup_p - \sum_{\tau=t_0}^{t-1} genCC_{p,\tau} \qquad \forall p, t \qquad (32)$$

3.4.2 Generation plant size and timing

Big-M type constraints impose bounds on newly added capacity $genCap_{p_{on},t}$. They multiply the binary decision variable $xGen_{p_{on},t}$ which is 1 if grid-connected plant p_{on} is built with some positive capacity in time t, with minimum required plant size $MinSize_{p_{on}}$ (33) and with an upper bound, either set to the maximum potential of each plant, $Sup_{p_{on}}$ for non-solar plants (34), or to a certain maximum capacity size $MaxSol$ for solar plants (35) (see section 3.7).

$$genCap_{p_{on},t} \geq xGen_{p_{on},t} \cdot MinSize_{p_{on}} \qquad \forall p_{on} \qquad (33)$$

$$genCap_{p_{on},t} \leq xGen_{p_{on},t} \cdot Sup_{p_{on}} \qquad \forall p_{on} \in P_{on}/P_{oS} \qquad (34)$$

$$genCap_{p_{oS},t} \leq xGen_{p_{oS},t} \cdot MaxSol \qquad \forall p_{oS} \qquad (35)$$

Moreover, a subset P_I of all on-grid generation plant P_{on} can only be built once during the planning horizon at a fixed capacity. Large-scale hydro dams or fossil fuel plants may serve as examples of such plants. This is modelled as follows:

$$\sum_{t} xGen_{p_I,t} \leq 1 \qquad \forall p_I \qquad (36)$$

3.4.3 Electricity generation

Annual electricity generation in each plant p in any time t, $gen_{p,t}$ cannot exceed the installed capacity of plant p in time t, calculated as the cumulative newly added capacity during the planning horizon until time t, $genCC_{p,t}$, plus the existing capacity parameter in time t_0, $ExSup_p$, multiplied by the plant's capacity factor CF_p as shown in constraint (37).

$$gen_{p,t} \leq \left(genCC_{p,t} + ExSup_p\right) \cdot CF_p \cdot 8760 \frac{h}{a} \qquad \forall p, t \qquad (37)$$

3.4.4 Environmental impact / carbon emission limit

The sum of carbon emissions in all time periods *t*, calculated as the product of annual generation $gen_{p,t}$ and life cycle CO_2 emissions CO_2Em_p of plant *p*, is required to be below allowed emission limit $MaxEm_t$ (38):

$$\sum_p gen_{p,t} \cdot CO_2Em_p \leq MaxEm_t \qquad \forall t \qquad (38)$$

3.5 Transmission constraints

3.5.1 Transmission line capacity

Similarly to expression (31), the cumulative transmission capacity on a line *l* between two adjacent cells, $transCC_{l,t}$, is calculated as the sum of newly added transmission capacity $transCap_{l,t}$ on line *l* up until time *t*.

$$transCC_{l,t} = \sum_{\tau=t_1}^{t} transCap_{l,\tau} \qquad \forall l,t \qquad (39)$$

Similar to expressions (33) – (35), big-M constraints impose minimum and maximum capacities on $transCap_{l,t}$. Binary decision variable $xTrans_{l_n,t}$ is multiplied by minimum capacity parameter *MinLine* (40), and by an upper bound, set to the maximum allowable share *MaxLine* of the greatest occurring average power demand, calculated as the maximum value of combined served business and domestic demand in any time *t*, divided by the number of hours in a year times an average transmission line capacity factor *CFTrans* (41):

$$transCap_{l_n,t} \geq xTrans_{l_n,t} \cdot MinLine \qquad \forall l_n \qquad (40)$$

$$transCap_{l_n,t} \leq xTrans_{l_n,t} \cdot MaxLine \cdot \max_t \left\{ \frac{ERTarBus_t \cdot \sum_c DemBus_{c,t} + ERTar_t \cdot \sum_c \left(DemU_{c,t} + DemR_{c,t}\right)}{8760 \frac{h}{a} \cdot CFTrans} \right\} \qquad \forall l_n \qquad (41)$$

Furthermore, it is assumed that it is optimal to build a certain transmission line l_n only once during the planning horizon (42):

$$\sum_t xTrans_{l_n,t} \leq 1 \qquad \forall p_I \qquad (42)$$

3.5.2 Electricity transmission

The annual electricity transmitted $trans_{l,ld,t}$, is bounded by its line capacity, calculated as the sum of added cumulative capacity $transCC_{l,t}$ and previously existing capacity $ExTr_l$ (43).[3]

$$trans_{l,ld,t} \leq \left(transCC_{l,t} + ExTr_{l,t}\right) \cdot CFTrans \cdot 8760\frac{h}{a} \qquad \forall l, ld, t \qquad (43)$$

3.5.3 Continuous grid

All power plants p_{nG} located in a non-connected cell c_n at baseline time t_0 are required to be connected to the national grid via the shortest path $SPGrid_{pnG,ln}$ from c_n to any cell which is connected to the transmission grid in time t_0 (see Appendix A for details). Let SP be the set of all (p_{nG},l_n) tuples where $SPGrid_{pnG,ln} = 1$. If a plant p_{nG} is built in time t, i.e. if binary variable $xGen_{pnG,t}$ is 1, then the model forces at least one variable $xTrans_{ln,t}$ up until time t to be 1 where line l_n is part of the shortest path from p_{nG} to the grid:

$$\sum_{\tau=t_1}^{t} xTrans_{l_n,\tau} \geq xGen_{p_{nG},t} \qquad \forall (p_{nG}, l_n) \in SP, t \qquad (44)$$

3.6 Distribution constraints

3.6.1 Intercell distribution capacity limit

To define the electricity sent to businesses, urban and rural households via distribution lines which connect different adjacent cells at baseline time t_0, denoted by $disBus_{c,t}$, $disU_{c,t}$, and $disR_{c,t}$, their sum is equated to the difference between incoming and outgoing intercell distribution $transD_{l,\,ld,t}$. It is sufficient to declare equation (45) only for cells c_n which are not connected via transmission lines at transmission voltage in baseline time t_0 as it is always optimal to use higher-voltage transmission lines for long-range electricity exchange between cells rather than low-voltage distribution (see section 2). Following the same logic, the demand served through $disBus_{cn,t}$, $disU_{cn,t}$, and $disR_{cn,t}$ in cells c_n is limited by what has been previously served in baseline

---

[3] Electricity can potentially flow in two directions *ld*, either from one specific adjacent cell to the other or vice versa. However, at any one set time, flow is only possible in one direction. As all transmission incurs a loss, it cannot be cost-optimal to have an electricity flow in both directions *ld* at the same time which is why no additional constraints are required to enforce this physical limit.

time t_0 (46) – (48), variable $transD_{l,ld,t}$ equals 0 where $ExTr_l$ equals 1 (49), and $disBus_{c,t}$, $disU_{c,t}$, and $disR_{c,t}$ are 0 in connected cells (50) – (52).

$$\sum_{l}\sum_{ld} transd_{l,ld,t} \cdot EBIn_{l,ld,c_n} \cdot DLoss_l \cdot ExTrD_l - \sum_{l}\sum_{ld} transD_{l,ld,t} \cdot EBOut_{l,ld,c_n} \cdot ExTrD_l = disBus_{c_n,t} + disU_{c_n,t} + disR_{c_n,t} \qquad \forall c_n, t \qquad (45)$$

$$disBus_{c_n,t} \cdot \left(1 - DLossBus_{c_n,t}\right) \leq ExBus_{c_n}, t \qquad \forall c_n, t \qquad (46)$$

$$disU_{c_n,t} \cdot \left(1 - DLossU_{c_n,t}\right) \leq ExUOn_{c_n}, t \qquad \forall c_n, t \qquad (47)$$

$$disR_{c_n,t} \cdot \left(1 - DLossR_{c_n,t}\right) \leq ExROn_{c_n}, t \qquad \forall c_n, t \qquad (48)$$

$$transd_{l,ld,t} \cdot ExTr_l = 0 \qquad \forall l, ld, t \qquad (49)$$

$$disBus_{c_c,t} = 0 \qquad \forall c_c, t \qquad (50)$$

$$disU_{c_c,t} = 0 \qquad \forall c_c, t \qquad (51)$$

$$disR_{c_c,t} = 0 \qquad \forall c_c, t \qquad (52)$$

3.6.2 Electricity distribution continuity

The model requires that any amount of electricity distributed for household consumption in a cell c in time t has to be at least as high as in previous time period $t - 1$.

$$elUOn_{c,t} \geq elUOn_{c,t-1} \qquad \forall c, t \qquad (53)$$

$$elROn_{c,t} \geq elROn_{c,t-1} \qquad \forall c, t \qquad (54)$$

$$elUOff_{c,t} \geq elUOff_{c,t-1} \qquad \forall c, t \qquad (55)$$

$$elROff_{c,t} \geq elROff_{c,t-1} \qquad \forall c, t \qquad (56)$$

3.7 Network resilience constraints

3.7.1 Maximum share of volatile electricity sources

The model imposes a limit *MaxVol* on the grid-connected installed capacity share from volatile sources (namely solar PV and wind) of total installed capacity in time t, calculated as the sum of newly added cumulative capacity until time t, $genCC_{pon,t}$ and the previously existing capacity $ExSup_{pon}$ at baseline time t_0:

$$MaxVol \cdot \sum_{p_{on}} \left(genCC_{p_{on},t} + ExSup_{p_{on},t}\right) \geq \sum_{p_{vol}} \left(genCC_{p_{vol},t} + ExSup_{p_{vol},t}\right) \qquad \forall t \qquad (57)$$

3.7.2 Geographical spread of solar plants

Most developing countries in Africa and South Asia are endowed with abundant solar insulation. In order to spread the volatility of solar irrigation over different parts of a country, the model imposes a maximum on-grid solar capacity *MaxSol* on the cumulative generation capacity in any cell, $genCC_{p,t}$:

$$genCC_{p,t} \leq MaxSol \qquad \forall p \in P_{oS}, t \qquad (58)$$

4. SOLUTION APPROACH

To solve the presented MO-MILP model, an ε-constraint approach is implemented. The idea is to convert both non-cost objective functions f_2 and f_3 to constraints by requiring them to not exceed a certain finite value ε_2 and ε_3, respectively. The model is then solved repeatedly for different ε_2 and ε_3 combinations to yield a Pareto Front of non-dominated solutions of the original MO-MILP problem.

While for some MO-MILP problems, ε-constraint approaches can be problematic, it is well-suited for the model presented in this paper for three main reasons. Firstly, both non-cost objective functions can be written as constraints which are naturally bounded between 0 and 100, with a straight-forward interpretation of the ε values, as follows: let $\varepsilon_{urbRur} = 100 - 100 \cdot \varepsilon_2$ be the minimum required degree of electrification equality measured as the difference between urban and rural electrification rates in any cell c in final time T. Furthermore, let $\varepsilon_{reg} = 100 - 100 \cdot \varepsilon_3$ be the minimum required degree of electrification equality measured as the difference between the electrification rate of any two different cells $c_1, c_2 \in C$ in final time T. Then, the ε-constraints can be written as follows:

$$erU_{c,T} - erR_{c,T} \leq 100 - \varepsilon_{urbRur} \qquad \forall c \qquad (59)$$

$$erR_{c,T} - erU_{c,T} \leq 100 - \varepsilon_{urbRur} \qquad \forall c \qquad (60)$$

$$erTot_{c_1,T} - erTot_{c_2,T} \leq 100 - \varepsilon_{reg} \qquad \forall c_1, c_2 \in \mathrm{C} \quad (61)$$

By definition of the electricity rate variables, the entire solution space is covered for $\varepsilon_{urbRur}, \varepsilon_{reg} \in [0,100]$. Crucially, this fact overcomes a weakness associated with the ε-constraint method where a sensible range of ε values is often not readily available *a priori*. Here, a value of 0 for ε_{urbRur} and ε_{reg} implies that the model requires the theoretically possible minimum sub-national electrification equality, whereas a value of 100 implies that the theoretically possible maximum electrification equality is enforced.

Secondly, this formulation rids the model of not continuously differentiable functions: The maximum functions in (2) and (3) are replaced with simple linear upper bound constraints. Furthermore, constraints (59) and (60) in combination replace the absolute value function in (2).

Thirdly, as sub-national electrification equality requirements are increased, the solution space becomes monotonically increasingly constrained. Hence, any optimal solution with a stricter sub-national electrification equality requirement is an upper bound for the optimal solution of a problem with a lower such requirement. This property is used in the solution algorithm, presented in Figure 2. It first solves an MILP, defined by expressions (1), (4) – (61), with a single cost objective for the case where electrification equality requirements are strictest (i.e. $\varepsilon_{urbRur} = \varepsilon_{reg} = 100$), and then uses the solution as an initial solution for a case where the electrification equality requirements are slightly relaxed by a fraction $k \in [0,100]$. Scalar k can be chosen depending on the desired granularity of the resulting Pareto Front as it corresponds to the step change in electrification equality requirements between different solutions that visualise the Pareto Front. To cover the four outer edges of the Pareto Front where ε_{urbRur} or ε_{reg} are either 100 or 0, k is best chosen such that $(100 \bmod k) = 0$, e.g. $k = 50, 33.\overline{3}, 25, 20, \ldots$. The initial solutions are updated as the ε values are updated to use the best available initial solutions in every run. Except for runs where either ε_{urbRur} or ε_{reg} are equal to 100, the algorithm provides two initial solutions to the MILP, one which was obtained from solving the MILP with ε_{urbRur} being fraction *k* greater than in the current run, and one with ε_{reg} being fraction *k* greater than in the current run. The smaller the *k* value chosen, the more single-objective MILP models have to be solved, however, the quality of initial solutions in each MILP solution run monotonically improves with smaller *k* values.

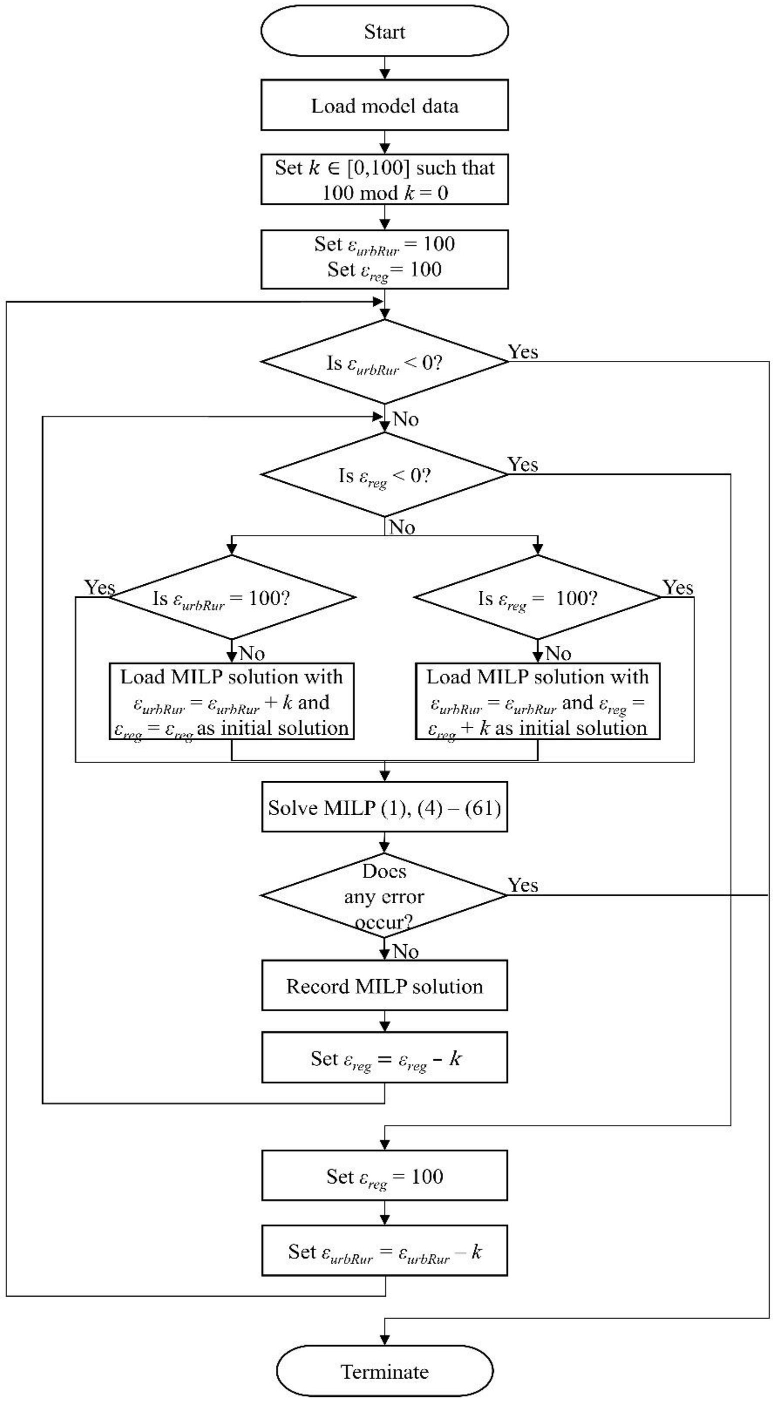


Figure 2: ε-constraint solution approach for MO-MILP problem

5. VALIDATION METHOD: INDICATIVE LOAD FLOW ANALYSIS

To indicate that the proposed energy networks for Uganda are valid, the Power Systems Analysis Toolbox (PSAT) 2.1.10 was used to conduct load flow analyses [65]. The networks of generation, loads and transmission lines obtained from the results of the optimiser were translated into the Matlab model format required for PSAT using a Python script. PSAT was run using Matlab 2016b. The only change was the addition of the slack bus to the model to enable the solver to converge. Load flow analysis has been used extensively to analyse power networks [66], usually where detailed network data is available, and it has been used in this work to examine the voltage profiles of the optimized networks.

For the case studied in this paper, the load flow model includes both the existing as well as the newly added generation and transmission line capacities for all 112 districts in Uganda in 2040, and demand loads for all 112 districts. Each district is defined as a bus in the network. A steady state power flow analysis (DC) was completed in PSAT, yielding the resulting voltage variations. The Newton Raphson Solver was used throughout. Per unit resistance and inductance values were also implemented for the transmission lines, and the system was simulated on a per unit basis throughout. As most of the lines do not exist yet, several load flow analyses were run with slight variations of resistance and inductance values. The model was constructed using phase estimates for the future demand loads, however these can be replaced by real values as the network develops over time. The load flow analysis should therefore be treated as indicative and useful for initial validation.

6. DATA: UGANDA CASE STUDY

To the best of our knowledge, this paper is the first to apply a long-term energy planning optimisation of a national electricity system considering generation and transmission to any sub-Saharan African country with low initial levels of power infrastructure. Hence, data for geospatial generation potentials, demand and demographics, costs and existing infrastructure had to be pooled from a variety of sources: To populate the model for the case of Uganda presented in this paper, 40 different sources providing data and/or relevant assumptions were used. Table 1 and Table 2 list the data sources for all scalars and parameters, respectively. Several parameters were not readily available and had to be calculated based on different data sources. To study implications for different generation options, the demand projections for the main case in this paper are comparably high, albeit significantly lower than Uganda's official development policy, Vision 2040 (see Appendix B for further details). The value for the discount factor DF_t follows from solving $DF_t = \frac{1}{(1+i)^{t-t_1}}$. Assuming an interest rate of $i = 5\%$ and $t_1 = 2020$, then $DF_{2020} = 1, DF_{2021} = 0.952, \ldots, DF_{2040} = 0.377$.

As of 2016, Uganda had roughly 35 million inhabitants and an available installed on-grid capacity of roughly 750 MW, with over 90% coming from hydropower at the source of the River Nile in Central Uganda [67]. Figure 3 shows Uganda's grid-connected power plants and operational transmission and distribution lines as of baseline time 2016, hinting at the existing electrification inequality in the country. Total transmission line length stood at 1,200 km, practically all of these lines had a voltage level of 132 kV [68]. Grid-connected electricity consumption was 2,567 GWh, 23% of which serviced domestic and 77% served business/industrial demand [69]. While not offering all technical details, geospatial data for the current power infrastructure (generation, transmission and distribution) is of comparably good quality in Uganda after Ugandan public sector stakeholders and German development agency GIZ published their GIS working group datasets in 2017 [68]. Uganda's electricity rate stood at roughly 20%, with stark electrification inequalities between urban (> 50 %) and rural (< 10 %) areas as well as between different regions (roughly 50 % in Central Uganda including Kampala, below 10 % in Northern Uganda) [1, 68]. The government has set an official target of 80% electrification rate by 2040, but has not specified which areas it intends to electrify and which not. It aims to attain middle-income status by 2040, increasing its per capita electricity consumption by a factor of 50 [70].

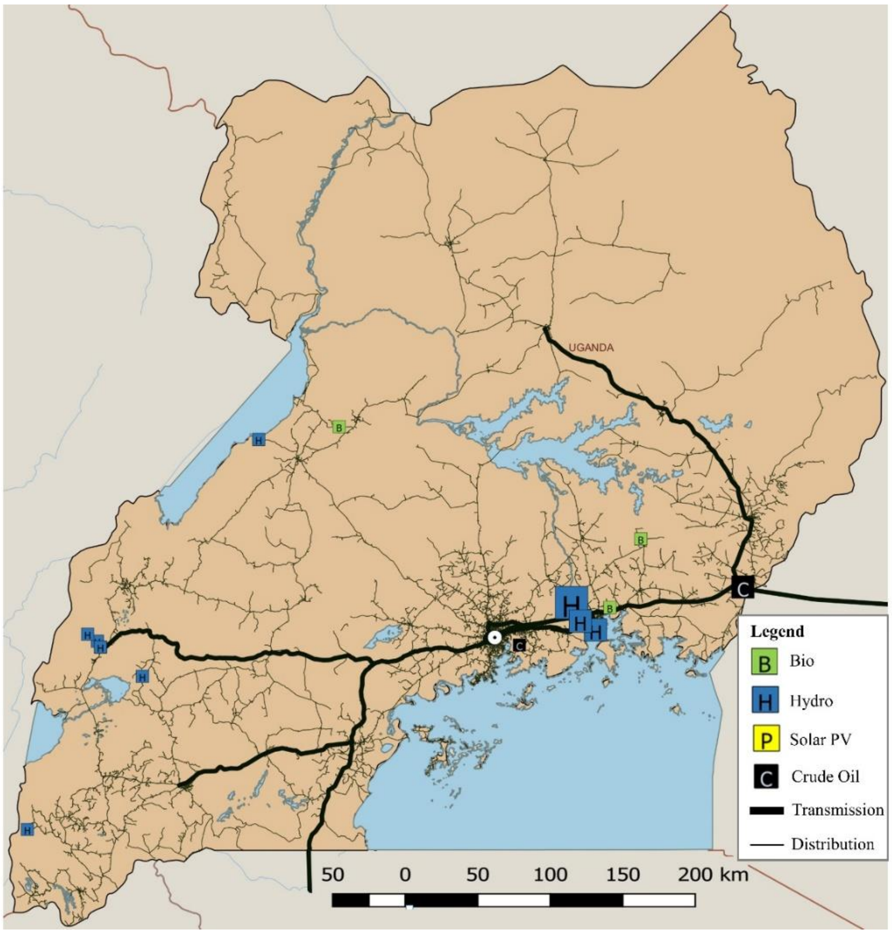


Figure 3: Uganda’s on-grid power plants, transmission and distribution lines in 2016 (data source: [68])

Table 1: Data values and sources for model scalars

Scalar	Value	Source
$CFTrans$	90 %	[71]
$CLkV$	1 %	[71]
$DOMSh$	2 %	[61, 72]
ε_{urbRur}	0 – 100	-
ε_{reg}	0 – 100	-
k	$33.\overline{3}$	(this paper)
$MaxLine$	25 %	(this paper)
$MaxSol$	500 MW	(this paper)
$MaxVol$	15 %	[73]
$MinLine$	28 MVA	[68]
$PDemRt$	0.000162	[67]
RM	150 %[4]	(this paper)
$TOMSh$	2 %	[61, 72]

[4] Relatively high value of reserve margin chosen due to the high share of renewables, especially hydro, in Uganda’s power system and the consequential low average availabilities during peak demand.

Table 2: Data and assumption sources for model parameters

Parameter	Source	Parameter	Source	Parameter	Source
CF_p	[74-78]	$DemU_{c,t}$	[1, 67, 69]	$ExUOn_c$	[67, 68, 71]
$CDisIR_{c,t}$	[64, 71, 79, 80]	$DLoss_l$	[67, 71]	$ExTr_l$	[68]
$CDisIU_{c,t}$	[64, 71, 79, 80]	$DLossBus_{c,t}$	[67, 71]	$ExTrD_l$	[68]
$CDisIROff_{c,t}$	[68, 81]	$DLossU_{c,t}$	[67, 71]	$GenEff_{pon}$	[78]
$CDisIUOff_{c,t}$	[68, 81]	$DLossR_{c,t}$	[67, 71]	$MaxEm_t$	[82]
$CGenI_{p,t}$	[74-76, 83]	$EBIn_{l,ld,c}$	[68]	$MinErBus_t$	[67, 71]
$CGenOM_{p,t}$	[74-76, 83]	$EBOut_{l,ld,c}$	[68]	$MinSize_{pon}$	[68, 78]
CO_2Em_p	[84, 85]	$ERTar_t$	[70]	$PCM_{p,c}$	[68]
$CTrIDis_{l,t}$	[71, 79, 80, 86, 87]	$ERTarBus_t$	[67, 70]	$PopR_{c,t}$	[1, 70, 88, 89]
$CTrIFix_{l,t}$	[71, 79, 80, 86, 87]	$ExBus_c$	[67, 68, 71]	$PopTot_t$	[1, 70, 88, 89]
$CTrIVar_{l,t}$	[71, 79, 80, 86, 87]	$ExROff_c$	[68]	$PopU_{c,t}$	[1, 70, 88, 89]
DF_t	(this paper)	$ExROn_c$	[67, 68, 71]	$SPGrid_{p_{nG},l_n}$	[44]
$DemBus_{c,t}$	[1, 67, 69, 70]	$ExSup_p$	[68]	Sup_p	[61, 67, 68, 74-76, 78, 83, 90-102]
$DemR_{c,t}$	[1, 67, 69]	$ExUOff_c$	[68]	$TLoss_l$	[44, 68, 71]

To analyse sub-national electrification inequalities, the spatial units were chosen to be relatively small. Uganda was divided into 112 cells corresponding to its 112 administrative districts. The average area of these cells is 1780 km^2 (roughly equalling a square with 42 km side length). As discussed in section 1, previous national-level generation planning studies have used a considerably smaller number of cells to divide a country's power system, usually ranging between 5 and 10 cells [4, 19, 31]. The subsequent results section presents results for both a 10-district case of Central Uganda as well as the national 112-district case, the latter allowing for a comparison with official Ugandan governmental targets for generation expansion. The year 2016 is set as baseline time t_0 and the year 2040 which coincides with Uganda's national development policy *Vision 2040* [70] is set to final time T. In 2016, only 35 of the 112 districts featured transmission lines. To reduce computational complexity, the model was implemented using 5-year time periods.[5]

7. Results and discussion

This section first presents the results of a case of 10 districts in Uganda in section 7.1, thus falling into the 5 – 10 cell interval used in recent long-term energy problem research [4, 19, 31]. Section 7.2 then discusses the results from the national-level, 112-district instance of Uganda. Section

5 As a consequence, the O&M cost equations are adjusted by a linear interpolation of generation, transmission and distribution infrastructure to accurately count every year within the 5-year time periods, multiplied with an annual discount factor.

7.2 closes with an indicative load flow analysis of the least-cost network to suggest the validity of the model results.

7.1 10-district model instance

The illustrative 10-district instance includes adjacent districts from Central and Eastern Uganda, ranging from Wakiso in the West to Jinja in the East and Nakasongola in the North (see Figure 4). The districts are centred around the two main demand centres in Uganda, Kampala and Wakiso, home to almost 40% of the entire urban population of Uganda in 2016. Five of the 10 districts were connected via transmission lines in 2016. A fictional electrification rate target for households and businesses was set to 50% in 2040. The instance includes 18 different potential new transmission lines between adjacent districts and 49 different potential new plants within the districts to meet any demand combination which meets the overall electrification rate targets.

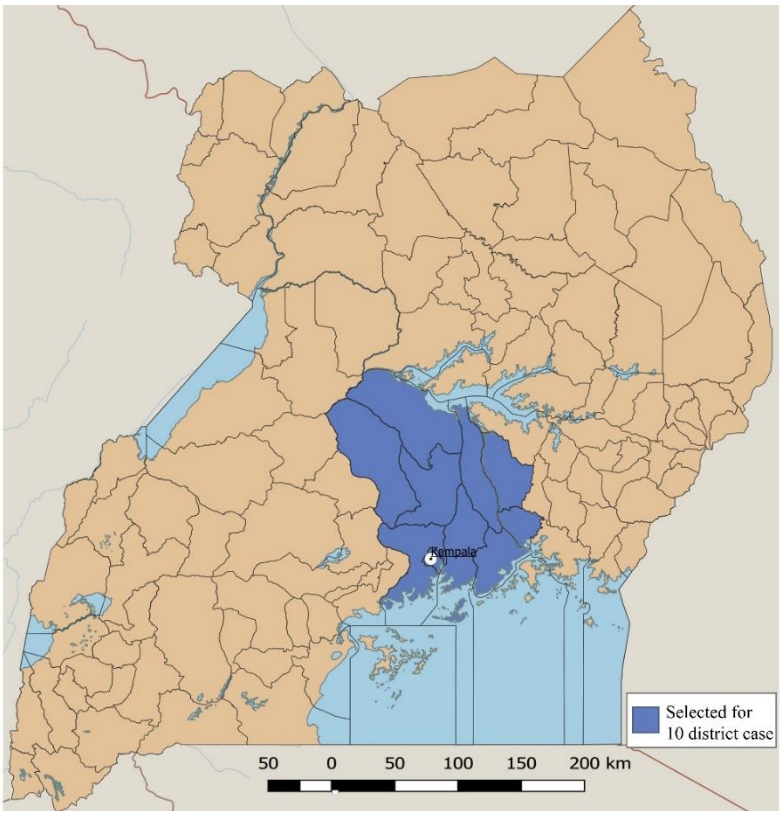


Figure 4: Uganda's 112 districts, and the ones selected for the illustrative 10-district instance (note that the capital Kampala is itself a district)

Using the solution approach described in section 4, the MO-MILP problem for the 10-district instance was solved to global optimality in 45 seconds using CPLEX 12.8 on a standard desktop computer with an Intel Core i5 3.30 GHz processor and 16 GB RAM for a granularity value $k = 33.\bar{3}$ (resulting in solving 16 MILP subsequently). Figure 5 shows the resulting comprehensive Pareto Front, interpolated between the 16 calculated solutions. Figure 6 provides the corresponding district-level and urban versus rural electrification rates for different electrification equality requirements. Non-surprisingly, it is cost-optimal to continue (and even increase) electrification inequality due to high population densities in Kampala and Wakiso vis-à-vis the other districts (Figure 6A). As ε_{reg} and ε_{urbrur} increase, regional as well as urban versus rural electrification rates converge.

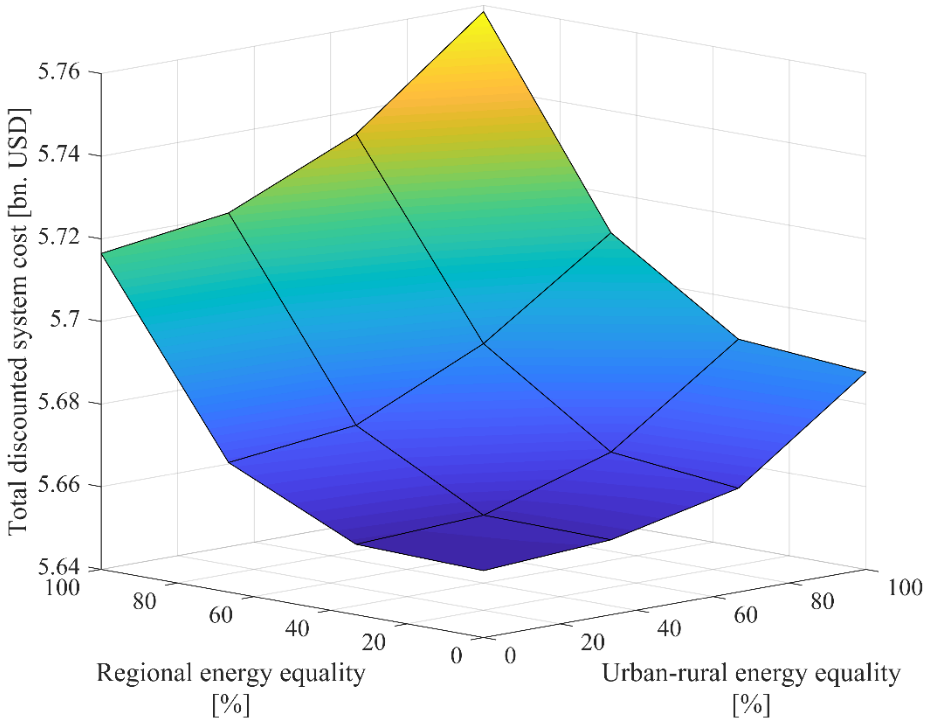
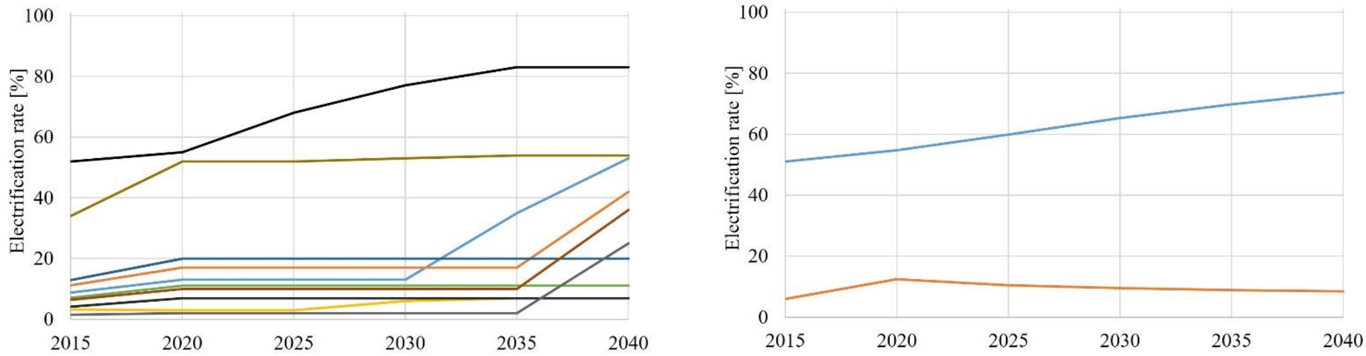
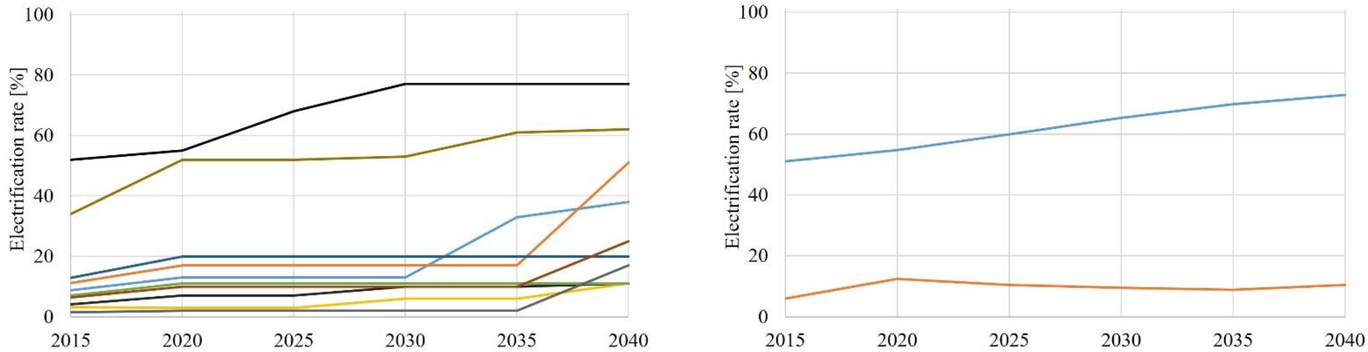


Figure 5: Entire Pareto Front for 10-district instance

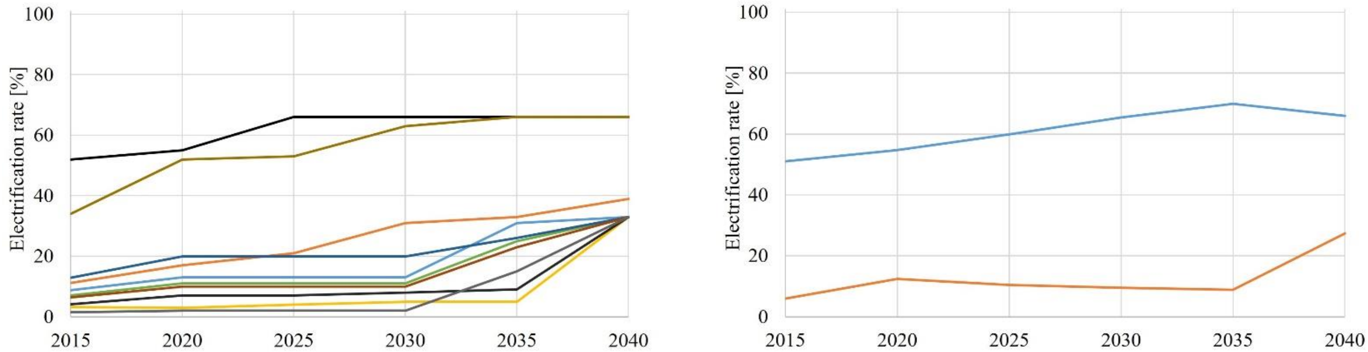
Notably, the Pareto Front indicates that achieving electrification equality between urban and rural areas within the 10 districts, as well as overall between the 10 districts, is possible at comparably small overall discounted cost increases of 2.1%. There are four main reasons for this, namely (1) the dominance of generation over transmission costs, (2) the abundance and cost-efficiency of different types of solar energy (Figure 7), (3) the low cost of off-grid generation due to cost reductions until 2040, and (4) comparably high population densities in Uganda, especially in the selected 10 districts for the illustrative case. As these reasons are shown to remain valid for the full country case, they are discussed in more detail in section 7.2.



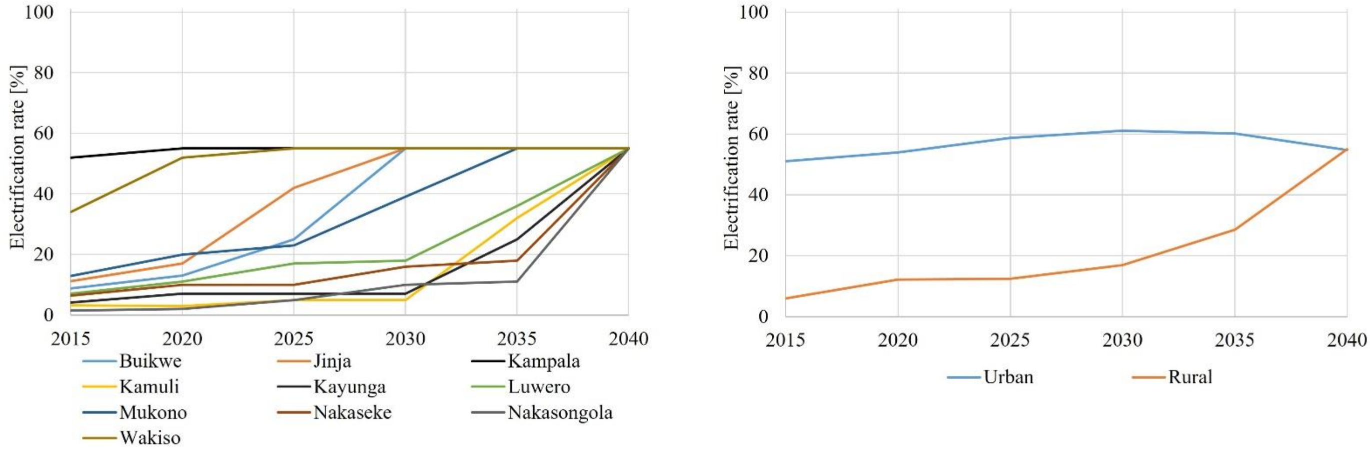
A: Regional and urban versus rural rates for $\varepsilon_{urbrur} = \varepsilon_{reg} = 0\%$



B: Regional and urban versus rural rates for $\varepsilon_{urbrur} = \varepsilon_{reg} = 33.\bar{3}\%$

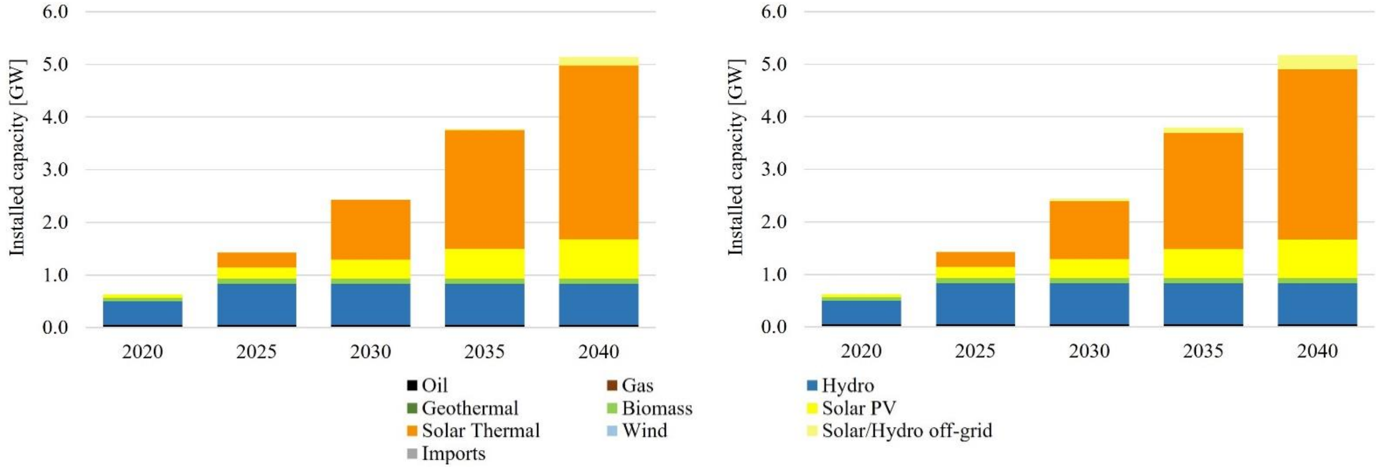


C: Regional and urban versus rural rates for $\varepsilon_{urbrur} = \varepsilon_{reg} = 66.\bar{6}\%$



D: Regional and urban versus rural rates for $\varepsilon_{urbrur} = \varepsilon_{reg} = 100\%$

Figure 6: Electrification rates for increasing regional and urban versus. rural equality requirements for the 10-district case



A: Optimal installed capacity for $\varepsilon_{urbrur} = \varepsilon_{reg} = 0\%$

B: Optimal installed capacity for $\varepsilon_{urbrur} = \varepsilon_{reg} = 100\%$

Figure 7: Optimal installed capacity for 10-district instance for no (A) and full (B) electrification equality requirements

7.2 112-district model instance

The full national case of Uganda features 112 distinct geographical cells, 278 different potential transmission lines connecting adjacent districts, and 483 different potential power plants within the districts to be built at time t meet any kind of demand combination which yields a given country-wide electrification rate at any time t. Consequentially, an extremely high combination of potential network configurations exists. Many of the feasible solutions are characterised by marginal cost differences between electrifying one specific district over another at a certain time. As for the 10-district case, the granularity value was set to $k = 33.\overline{3}$, and CPLEX 12.8 was used to solve the problem on the same machine as described in section 7.1. CPLEX solved the first MILP of the solution approach described in section 4, i.e. the case where $\varepsilon_{urbrur} = \varepsilon_{reg} = 100\%$ and no initial solution exists to be utilised, to within 1% of global optimality within roughly 25 minutes of runtime, while all other 15 MILPs where at least one feasible initial solution was provided were solved to within 1% of global optimality at the root node within 90 seconds of runtime. An optimality gap of 0.5%, a value significantly below the degree of uncertainty present in the available data (see section 6), was set to ensure practical solution times.

7.2.1 Non-dominated solutions of multi-objective problem

The resulting Pareto Front is presented in Figure 8, the corresponding, steadily converging electrification rates for different regions and urban versus rural areas are shown in Figure 9. As these figures show, it is cost-optimal for high electrification inequality to continue (and in the first decade, even increase) in Uganda if no electrification inequality minimisation criterion is imposed. This result is consistent with the consequences of Uganda's current electrification approach which is biased towards those households who already are close to the national grid [103]. The modelling results suggest that in the purely cost-minimal case, the capital Kampala is immediately fully electrified in 2020, Eastern Uganda which is home to most of the generation today is electrified next, while electrification rates in Northern and Western Uganda increase much more slowly until 2040. If, however, the model forces increasing electrification equality (i.e. ε_{urbrur} and ε_{reg} approach 100%), then the electrification rates converge for all regions much quicker. In this case, between 2035 and 2040, almost all new connections are located in rural areas and urban population growth outpaces urban connection rates.

However, the resulting cost increase incurred through forcing sub-national electrification equality in Uganda of roughly 3% is comparably low. Similarly to the 10-district case, this is due to four main reasons. It is important to note that several of which are highly specific to the Ugandan case. Firstly, in the cost-minimal solution, the discounted total generation costs make up 84% of the total system costs of roughly 24 bn. USD. Hence, the model chooses a similar generation mix independent of where the electricity had to be sent to achieve higher electrification equality (see section 7.2.2). Specifically, switching away from cheap but fixed-location hydro, biomass, fossil fuel or geothermal plants is more expensive than incurring additional transmission costs to connect these sources to the grid. Where these resources are comparably far removed from the grid, there is an added benefit of building new transmission lines to be used to electrify districts between the plants and the grid.

Secondly, the abundance of solar insolation in Uganda allows the model to incur similar generation costs for different generation locations by shifting solar PV, CSP plant and solar off-grid capacities from one district to another at little extra cost (see section 7.2.3 and Table A in Appendix C). For instance, the cost-optimal solution with no electrification equality requirement turns Kasese district, located at the boarder to the Democratic Republic of Congo in Western Uganda and endowed with high solar insolation, into an important generation hub for Southwest Uganda, installing 398 MW solar PV, 353 MW CSP and 71 MW solar off-grid. Achieving full electrification equality with all districts having an 80% electrification rate in 2040 implies shifting some of this capacity elsewhere: For $\varepsilon_{urbrur} = \varepsilon_{reg} = 100\%$, solar PV in Kasese is reduced to 382 MW, CSP is reduced to 241 MW and solar off-grid to 53 MW (Table A). For instance, in Nakasongola district, the optimal CSP capacity increases from 159 MW to 226 MW. As the abundance of solar resources and the rapidly falling costs of solar PV and especially CSP (see Appendix B) lead to high shares of both technologies in the optimal solution, this is a cost-effective strategy to help achieve electrification equality in Uganda.

Thirdly, off-grid technologies are projected to continue their significant cost decrease. As current cost levels already render them a cost-competitive mode of electrification in many rural areas today, they play a key factor in helping to close the cost gap between urban and rural electrification going forward. The projected cost reductions significantly decrease the cost of forcing electrification equality in 2040. In the optimal solution, the model chooses 15% of all electricity consumed in Uganda to come from off-grid sources in 2040. The requirement of electrification equality can be met in a cost-efficient way by increasing the off-grid share and, even more so, heavily shifting around off-grid capacity between districts (Table A).

Fourthly, Uganda's comparably high population density of 208 people per square km is projected to almost double by 2040, further decreasing the per person cost of electrification.

These results indicate that the Ugandan government and its international development partners can dramatically reduce electrification inequality in Uganda at little extra total system cost if they allocate spending accordingly. Shifting solar capacities as well as transmission and distribution expansion to regions with low access today, and significantly increasing off-grid electrification present cost-efficient measures to curtail inequality and provide more equal opportunities to all Ugandans.

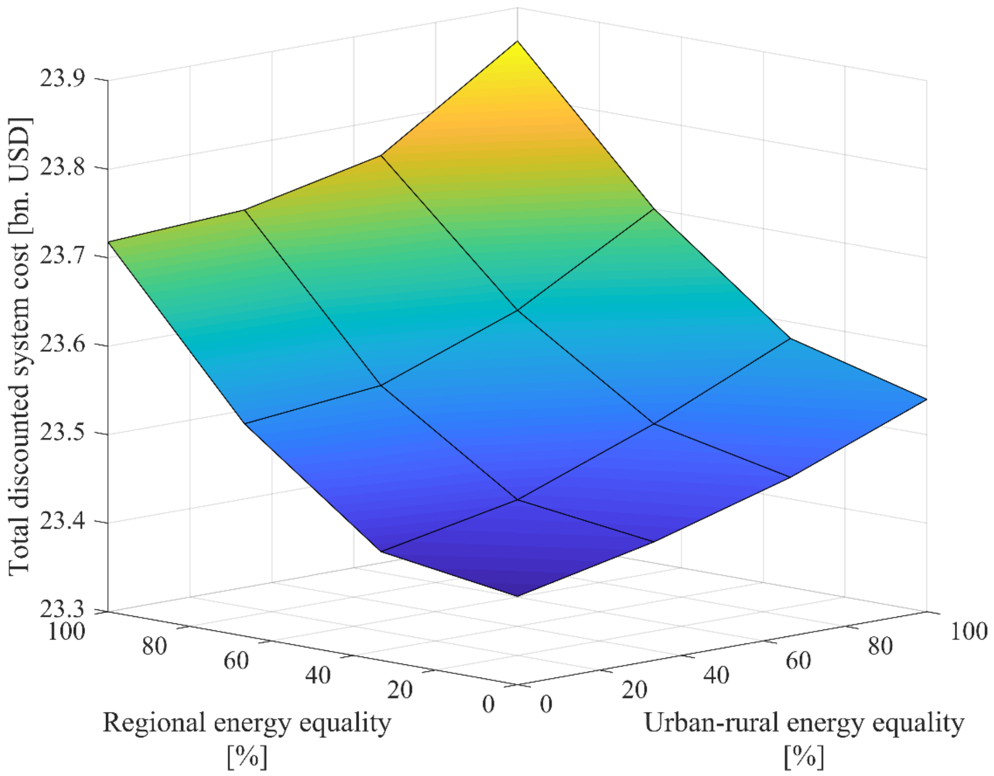
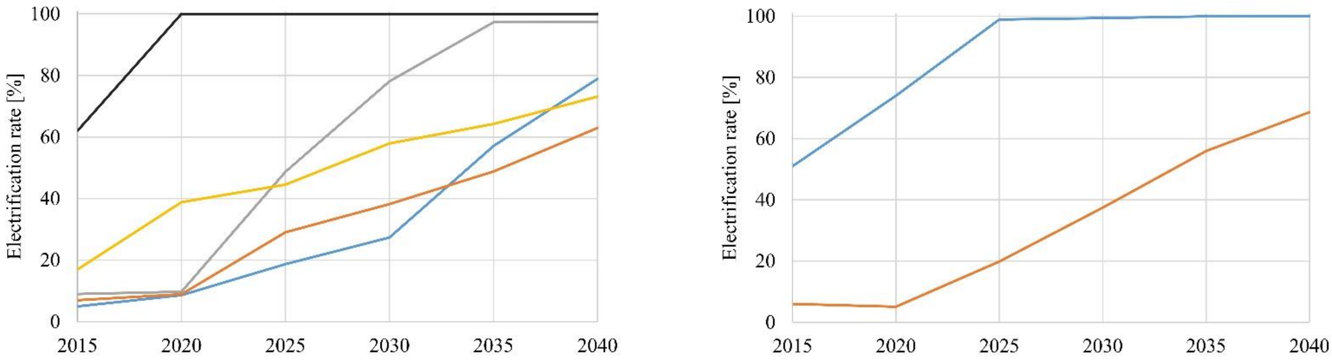
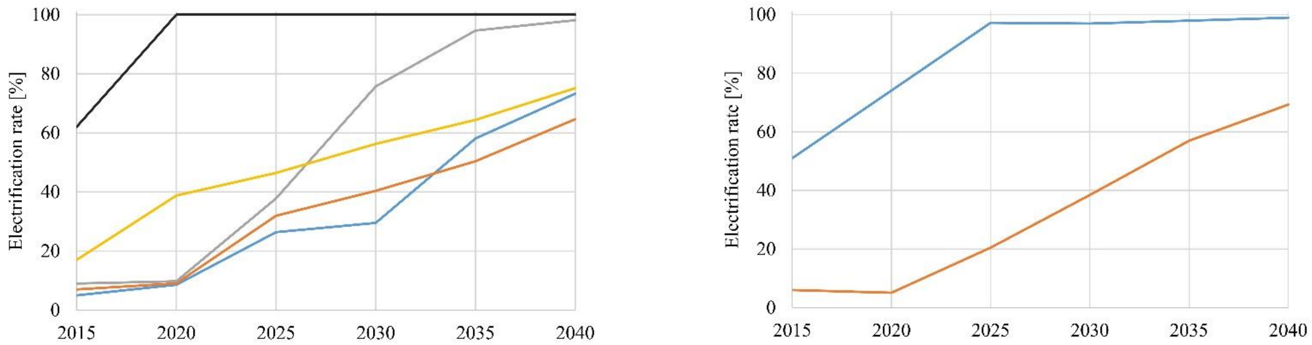


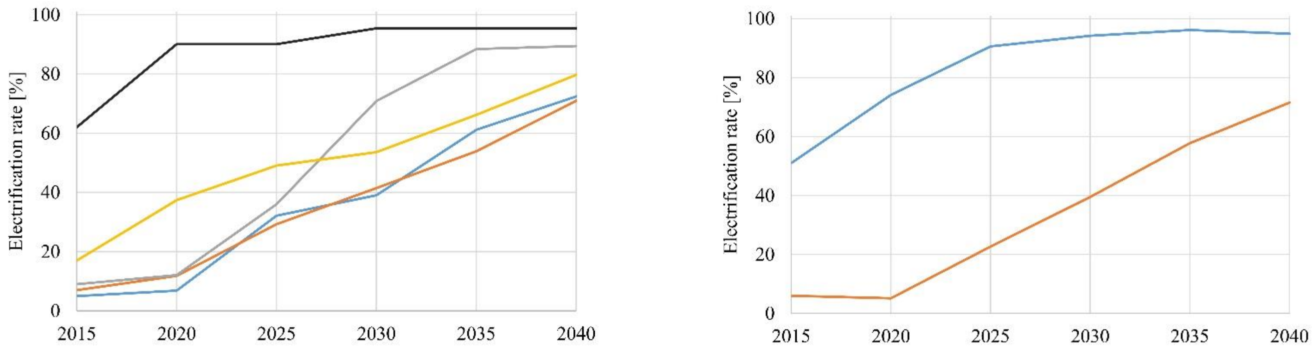
Figure 8: Entire Pareto Front for full national Ugandan case



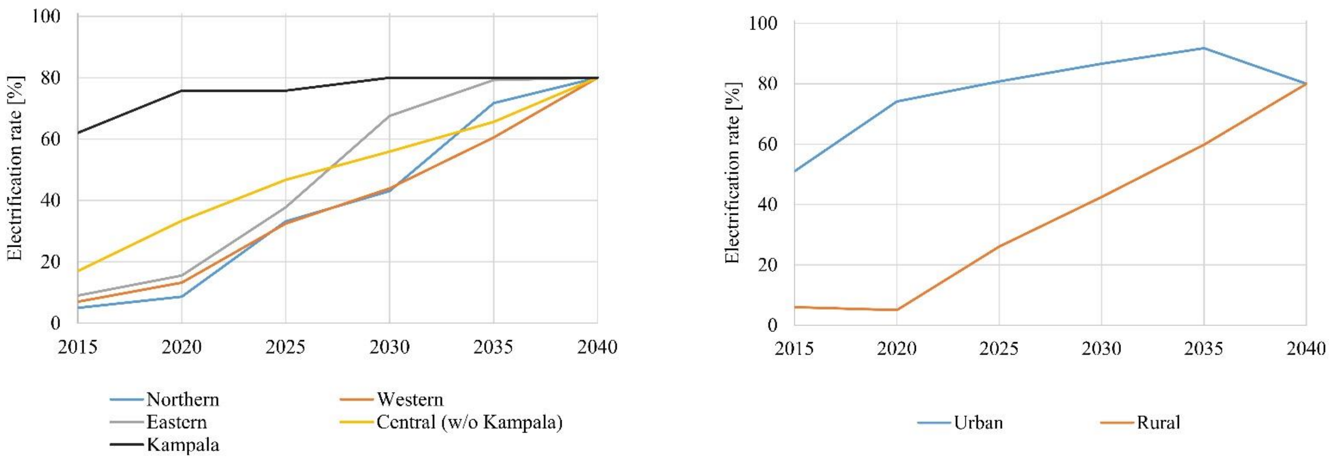
A: Regional and urban versus rural rates for $\varepsilon_{urbrur} = \varepsilon_{reg} = 0\%$



B: Regional and urban versus rural rates for $\varepsilon_{urbrur} = \varepsilon_{reg} = 33.\overline{3}\%$



C: Regional and urban versus rural rates for $\varepsilon_{urbrur} = \varepsilon_{reg} = 66.\overline{6}\%$

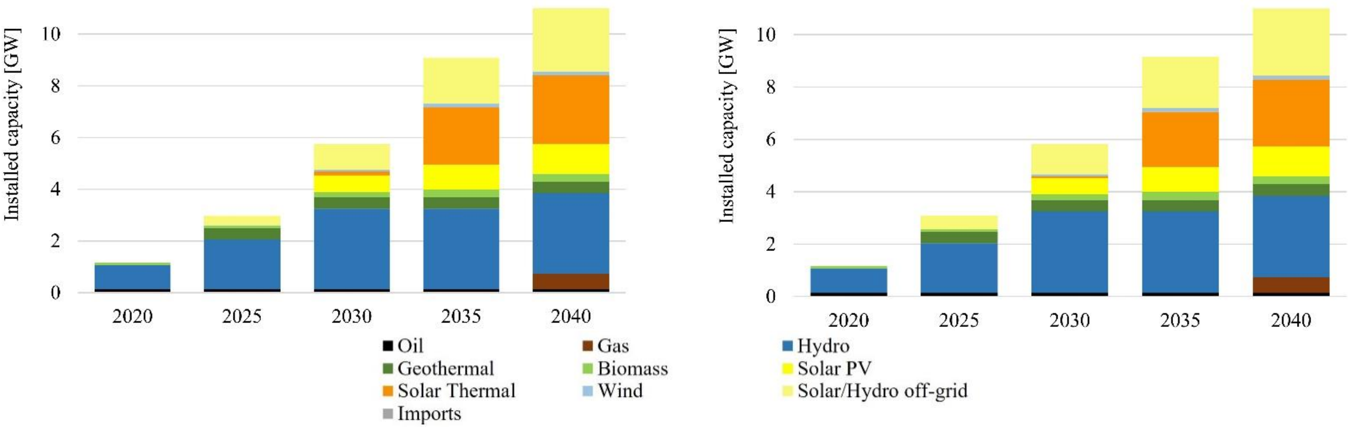


D: Regional and urban versus rural rates for $\varepsilon_{urbrur} = \varepsilon_{reg} = 100\%$

Figure 9: Electrification rates for increasing regional and urban versus. rural equality requirements for full national case

7.2.2 Optimal installed capacity (high demand case)

Figure 10 highlights the optimal installed capacity over time. As Appendix B suggests, the demand assumptions for both households and businesses are comparably high (albeit much lower than Ugandan official electricity consumption targets). The resulting capacity addition merit order, however, is mainly independent of demand estimations: At first, Uganda's cheapest generation option is to develop its hydro resources on the River Nile, a resource which offers roughly 2.5 GW in addition to what is installed already. The next cheapest options are biomass (roughly 350 MW), geothermal (roughly 440 MW), the limited wind energy in Northeastern Uganda (roughly 140 MW), and solar PV (significantly higher potential than any conceivable demand). As solar PV is constrained by its intermittency, CSP with storage is the next cheapest option capable of providing 24 hour baseload, again with almost unlimited potential compared to any reasonable demand forecast. In the example demand scenario presented in Figure 10, falling CSP prices lead to a surge of CSP installations from 2035. While the Ugandan government's current focus of hydro is supported by this paper, the importance of solar PV, and especially CSP as well as off-grid technologies are at odds with the government's plans to expand nuclear energy (see section 8).



A: Optimal installed capacity for $\varepsilon_{urbrur} = \varepsilon_{reg} = 0\%$ **B:** Optimal installed capacity for $\varepsilon_{urbrur} = \varepsilon_{reg} = 100\%$

Figure 10: Optimal installed capacity for full national case for no (A) and full (B) electrification equality requirements

7.2.3 On-grid versus off-grid connection results

Figure 10 also shows a significant amount of off-grid capacity in Uganda. Falling prices in the off-grid sector, especially for small and medium-sized solar systems sufficient to power any household appliance, imply that these systems are already cost-competitive with, and in most cases in the future, cheaper than grid-expansion. Table 3 presents the total number of household connections throughout the planning horizon, split by main region and on-grid versus off-grid. These figures include roughly 1 million existing connections in 2017. While exact cost developments are difficult to predict, the results indicate that the share of off-grid connections is set to rise significantly in all regions and all years. Pushed by the continued cost decrease of solar off-grid systems and Uganda's strong population growth, the projected overall cost-optimal share reaches two-thirds by 2040. These results strongly challenge the Ugandan government's official electrification policy which focuses heavily on grid-expansion (see [70] and [67]).

Table 3: Total number of household connections on-grid and off-grid in cost-minimal solution [million]

	2020		**2025**		**2030**		**2035**		**2040**	
Region	On-grid	Off-grid	On-grid	Off-grid	On-grid	Off-grid	On-grid	Off-grid	On-grid	Off-grid
Northern	0.10	0.04	0.32	0.05	0.37	0.24	0.40	1.03	0.42	1.75
Western	0.15	0.08	0.53	0.18	0.56	0.51	0.57	0.98	0.58	1.64
Eastern	0.13	0.12	0.34	0.85	0.38	1.78	0.38	2.60	0.38	2.88
Central	0.73	0.04	0.97	0.04	1.11	0.41	1.26	0.69	1.32	1.21
Kampala	0.45	0.00	0.62	0.00	0.83	0.00	1.09	0.00	1.10	0.31
Sum	1.57	0.28	2.78	1.12	3.26	2.94	3.70	5.30	3.80	7.78
Share [%]	85	15	71	29	53	47	41	59	33	67
Electrification rate [%][1]	25		40		55		70		80	

[1] The electrification rate was set as a modelling parameter a priori (see section 3.2), the 80% in 2040 match Uganda's official electrification target in the governmental Vision 2040 policy [70]

7.2.4 Network design and indicative load flow analysis

Figure 11 and Figure 12 illustrate the resulting optimal network design for no and full electrification equality requirements in Uganda in 2040, respectively. In addition, Table A in Appendix C lists the optimal installed generation capacity in 2040 for all 112 districts by technology for the cases of forcing no electrification equality, i.e. $\varepsilon_{urbrur} = \varepsilon_{reg} = 0\%$, and for full electrification equality, i.e. $\varepsilon_{urbrur} = \varepsilon_{reg} = 100\%$.

In either case, the main power highways stretch from the various large-scale hydro dams along the River Nile towards the industrial epicentres in Central Uganda and Kampala, specifically. The relative dominance of these lines becomes more pronounced the lower the total demand projection is. CSP in Central Uganda as well as solar PV in Eastern Uganda are found to act as crucial technologies to combine demand centres with close-by generation to minimise transmission requirements and associated losses. Crucially, in contrast to current governmental efforts to expand medium-voltage distribution lines [69], this paper finds the expansion of high-voltage transmission lines to be superior in most cases due to lower loss implications of high-cost generation. Furthermore, off-grid technologies, greatly dominated by solar PV and battery combined systems, play an instrumental role in nearly all districts in the cost-optimal solutions, crucially decreasing the need for distribution infrastructure. This effect becomes slightly more pronounced as electrification equality is forced as more rural households are being electrified with off-grid solar rather than urban households who rely more strongly on grid electrification. Due to reasons discussed in section 7.2.1, it is not surprising that the networks in Figure 11 and Figure 12 are similar.

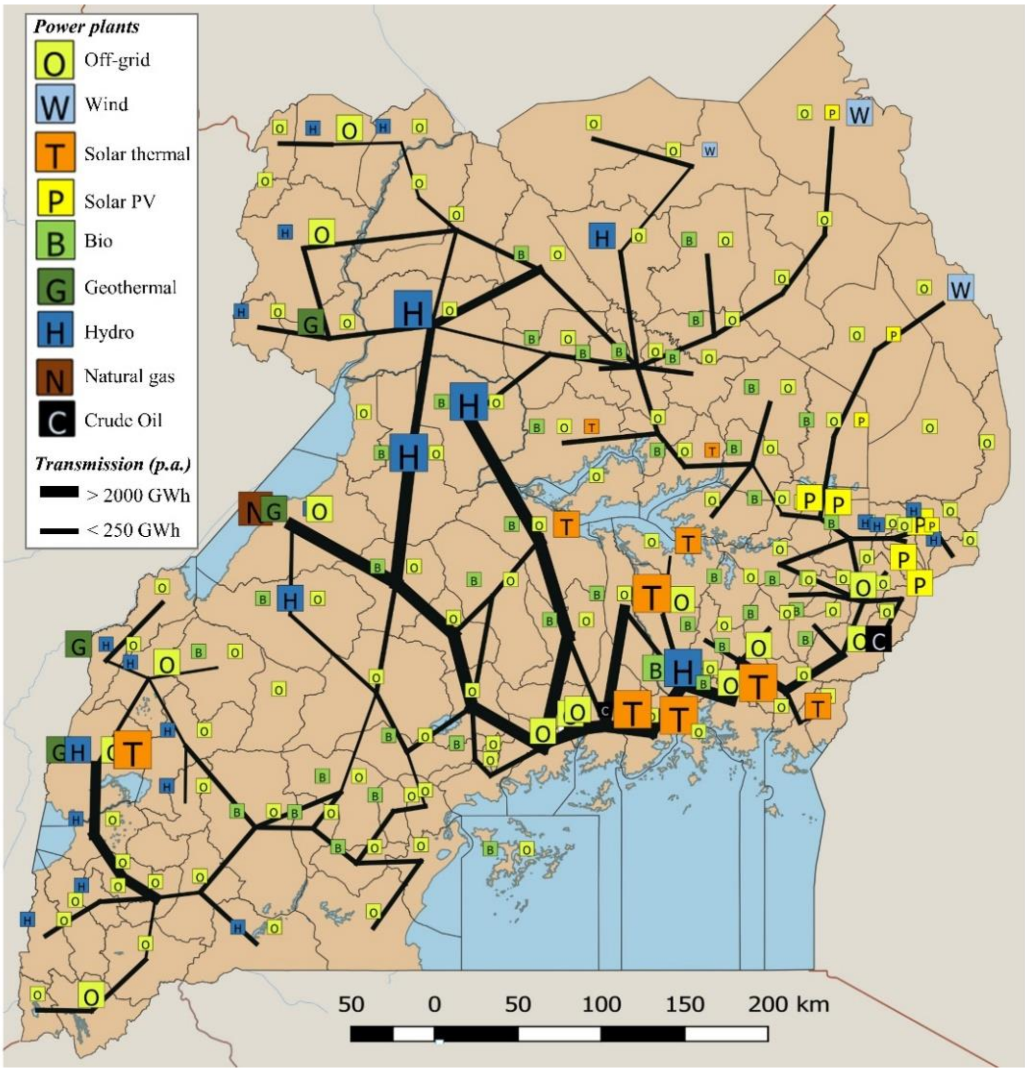
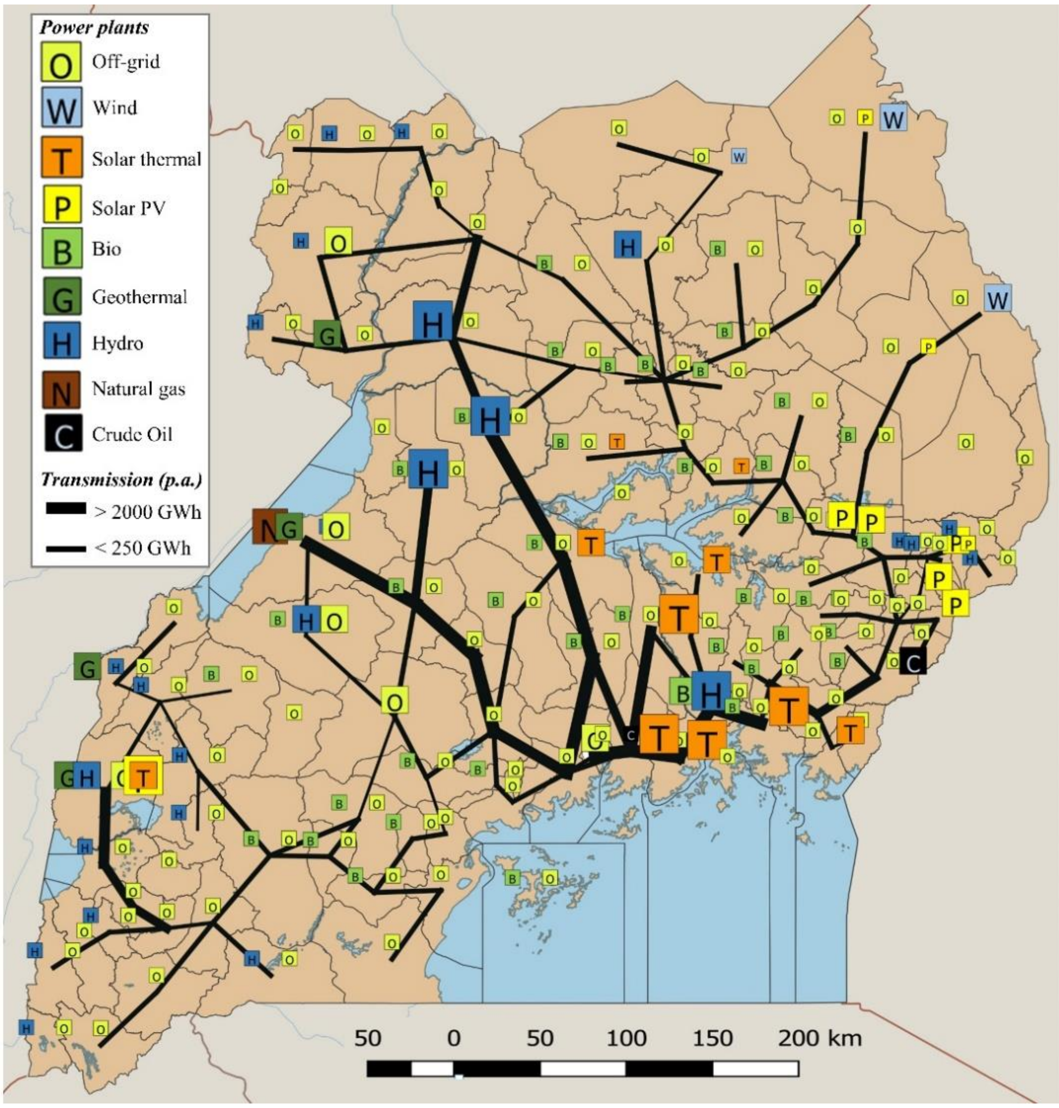


Figure 11: Optimal network configuration for no electrification equality requirements (i.e. $\varepsilon_{urbrur} = \varepsilon_{reg} = 0\%$)



B: Optimal installed capacity for $\varepsilon_{urbrur} = \varepsilon_{reg} = 100\%$

Figure 12: Optimal network configuration for full electrification equality requirements (i.e. $\varepsilon_{urbrur} = \varepsilon_{reg} = 100\%$)

Finally, the results from an indicative load flow analysis as described in section 5 are shown in Figure 13. The steady state power flow analysis (DC) was performed on the least-cost network shown in Figure 11. The network model converged and the resulting voltage variation, which arise from the phases estimates for the network, was limited: The p.u. minimum voltage of those districts connected to the network was 0.950 and the maximum p.u. voltage was 1.046. Changing the resistances and inductances assumed for the newly constructed lines had no noteworthy effect on the voltage profile of the network. District 24 is completely disconnected from the network, with no transmission lines through, or connection to the main network, and hence shows up as zero voltage. Given the long-term planning horizon until 2040 and the associated uncertainty, the network model is simplified given the paucity of empirical data, hence the associated voltage profile results should be treated as being indicative.

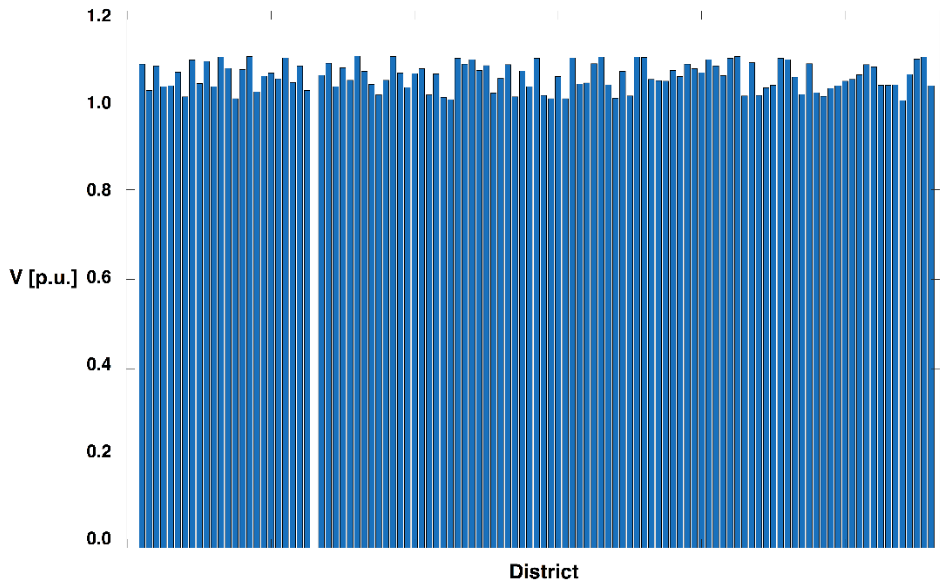


Figure 13: Per unit voltage magnitude profile for all buses (districts) from indicative load flow analysis

8. COMPARISON WITH UGANDA'S OFFICIAL GENERATION EXPANSION PLAN

To compare the official capacity targets from Uganda's governmental development policy "Vision 2040" [70] with the model presented in this paper, an additional demand scenario is studied. This demand scenario follows from assuming the Uganda's official policy target of a 3,668 kWh per capita consumption case in 2040.

Figure 14 compares Uganda's Vision 2040 capacity targets with the model results using this demand scenario. The higher total installed capacity resulting from the model is due to the lower average capacity factor of the generation mix suggested by the model compared to the one from the governmental target generation mix. It should be noted that this high-end demand scenario, although it is the official governmental target, is highly unlikely to be attainable as it would require an average 20% per annum electricity consumption increase in every year between 2018 and 2040. Yet even if this high-demand scenario were to be realised, the model results differ fundamentally from the official governmental targets. Most dramatically, while the government plans to have a noteworthy 24 GW of nuclear energy installed in Uganda in 2040, the model does not find nuclear to be optimal in any demand scenario. In fact, the governmental plan is found to be infeasible by the model as it far exceeds a realistic estimation of nuclear potential (and, to a lesser degree, the fossil fuel potential) in Uganda by 2040. CSP is found to be a cheaper baseload option for Uganda (see also Appendix B). In addition, CSP is a favourable technology in terms of environmental risk, local content potential (as mirrors and solar tracking devices can be manufactured locally), the technology's potential to foster electrification equality and market opportunity due to its projected global growth in the coming decades.

The model also shows that in addition to the requirement to expand the grid, a significant degree of off-grid solutions are cost-optimal to electrify mainly rural areas in Uganda. The model results indicate that off-grid technologies are the dominant form of electrification in rural Uganda. Due to its cost reductions, this remains true despite the country's comparably high population density in 2040. These findings furthermore challenge Uganda's official electrification plans which aim to achieve its 80% electrification rate almost exclusively by expanding the grid [70]. The widespread underrepresentation of off-grid technologies has recently been shown to by systemic among many developing countries [104]. By expanding electricity planning to incorporate both the generation and transmission system as well as different distribution options, this paper lends further support to the call for national energy plans to place more emphasis on off-grid electrification in sub-Saharan Africa.

In summary, if we assume that Uganda's official Vision 2040 capacity target was feasible, the model solution with CSP and off-grid technologies presented in this paper could be estimated to save roughly $ 4 – 6 bn. in discounted overall system cost compared to the Vision 2040 plan.[6]

In addition, while Ugandan policies have heavily focused on generation capacity additions, it is crucial to note that for Uganda to realise widespread electrification, there needs to be a greater emphasis on expanding transmission infrastructure. The current goals of transmission line additions fall considerably short of what is needed, especially in the time until 2025. The transmission company UETCL is known for being underfunded. Ironically, despite the cost dominance of generation versus transmission technology, the evacuation of power is a prime concern in Uganda at the moment [105].

---

[6] This number would be higher if the full cost reduction potential of CSP as projected by IRENA materialises, see appendix B1.

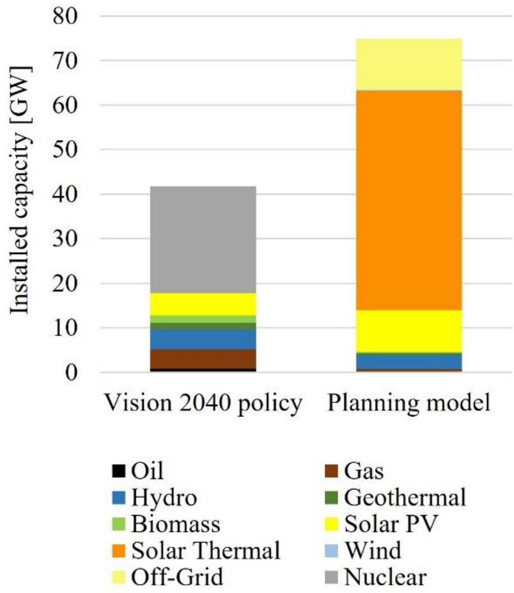


Figure 14: Uganda's official capacity target ("Vision 2040") versus model results for similar annual kWh demand assumptions in 2040

9. Conclusion

National power systems in many developing countries are characterised by substantial suppressed electricity demand due to low connection rates, highly unequally distributed energy access, and the relevance of both on-grid and off-grid electrification approaches. This study designed the first integrated, multi-criteria optimisation model for long-term national-level energy planning tailored to developing countries with low initial electricity infrastructure. The model successfully generalised the generation expansion planning problem in three areas: Firstly, by reformulating the demand constraints in terms of electrification rates which can take any value between 0 and 100%, the model was able to accommodate and plan for suppressed demand. Second, the model defined sub-national electrification inequalities as a simultaneous optimisation objective to cost minimisation. Thirdly, it integrated generation and transmission planning with a linear distribution approximation to determine the optimality of on-grid versus off-grid electrification aggregated at the level of a geographical cell. The paper suggested a solution algorithm based on the ε-constraint method which utilises the nature of the mathematical formulation of the social (i.e. non-monetary) objectives. The model's application to the case of the Ugandan national power system showed that the model is able to accommodate the specific challenges of this problem. The proposed solution algorithm was found to perform well and was able to indicate the problem’s entire Pareto Front of non-dominated solutions. A load flow analysis has indicated the feasibility and stability of the resulting network designs.

The model results of the numerical case example of Uganda have generated a number of novel insights. In contrast to the government’s focus on grid-extension which would imply sub-national electrification inequality to remain high in Uganda, the model results have shown that widespread electrification equality can be achieved in Uganda at comparably little extra relative total system cost: Forcing an electrification rate of 80% in all urban and rural areas throughout the country increases the total discounted system costs by only 3% compared to the case where no electrification inequality restrictions are in place. This is driven by the dominance of generation over transmission and distribution costs, the abundance of cheap solar energy, significantly decreasing costs of off-grid technologies up until 2040, as well as Uganda’s comparably high projected population density in 2040. Uganda’s strategic priority of on-grid over off-grid electrification mirrors a more general trend in developing countries [104]. Yet, this paper suggests that it is cost-optimal to provide a two-thirds of connections by off-grid technologies by 2040, despite the fact that the assumed per capita demand is comparably high. Furthermore, this paper has shown that Uganda’s official generation expansion targets are infeasible and, if they had been feasible, would be cost-inefficient. If one were to use Uganda’s official per capita demand targets, replacing the government’s planned nuclear expansion with solar concentrated power and focusing more strongly on off-grid electrification would lead to savings of 4 – 6 bn. USD in total discounted system costs until 2040.

In general terms, this paper has shown that improving planning approaches by using spatially explicit models that consider generation, transmission and distribution comprehensively, can reveal cheaper and more equal ways of electrification for countries with low electrification access rates. Further improvements regarding the geospatial resolution and the accuracy of demand estimations are required in developing countries to best plan national power systems for the long term.

ACKNOWLEDGEMENTS

The authors would like to acknowledge excellent comments and suggestions from Peter Twesigye, Hans Pirnay, Yusuf Kiranda, Alex Money, Gunes Erdogan, Kevin Wheeler, Max

Walter and Daniel Junglas, as well as from the audiences of the 2018 Energy Systems Conference in London, UK, and the 2018 Practical Challenges of Sustainable Electrification in Africa Conference in Oxford, UK. Dimitris Mentis from KTH Stockholm, Peter Twesigye from UMEME Ltd. Uganda and Martin Kretschmer from GIZ Uganda generously shared their raw data. This research has been funded in part by the Engineering and Physical Sciences Research Council (EPSRC) grant EP/M507982/1 awarded to the University of Bath, United Kingdom. The research has been approved by the Mbarara University of Science & Technology Research Ethics Committee, and fully permitted by the Uganda National Council for Science and Technology (UNCST) under reference number SIR7ES. The authors declare no competing interests.

APPENDIX A – SHORTEST PATH HEURISTIC

To ensure a silo-free grid, all plants p_{nG} which the model chooses to newly build in a cell that was not served through the transmission grid in baseline period t_0 (the year 2016 in the numerical examples) need to be connected to the national grid. The shortest path heuristic requires all plants p_{nG} to be connected via all lines l which form the shortest path from the plant's cell to any cell which is connected to the grid in t_0. (implemented in equation (45)). The shortest path problem is a classic optimisation problem which has been described in great detail before [106] and can be solved efficiently as a separate LP for all combinations of p_{nG} and all connected cells c_c to find the shortest path from each plant p_{nG} to the grid. The results are then used as an input parameter to the MO-MILP problem. The results are then used as an input parameter $SPGrid_{pnG,ln}$ to the present MO-MILP problem which is 1 if transmission line l_n is part of this shortest path to the grid, and 0 otherwise. Reference [44] describes this approach in mathematical detail and applies it to another energy planning problem. While this heuristic can lead to the model suggesting building two separate lines from two close, un-electrified districts to the grid where in fact, only one line would be required, it considerably reduces the numerical complexity of the problem. Namely, it avoids a model structure where the optimal transmission lines required for newly built plant p_{nG} depend on the status of all other transmission lines l_n.

APPENDIX B – DATA DETAILS

B.1 Cost data

Generation investment as well as O&M cost data for all major on-grid and off-grid technologies in Africa are available from IRENA (see Table 2). IRENA's forecast for module cost development have been adopted. Where data for Uganda specifically was not available, Eastern African or sub-Saharan African averages were used. It is noteworthy that a recent IRENA report cites dramatic cost decreases for CSP [83]. Indeed, the 2017 auction for the Copiapó Solar Project in Chile produced a winning bid of 0.063 USD/kWh for a 260 MW 24-hour baseload CSP plant. Later in 2017, another Chilean auction received a CSP bid for under 0.05 USD/kWh. While similarly assuming a rapid cost decline for CSP, the reductions used in this study are more conservative than what follows from the IRENA figures. This study assumes an equivalent levelised cost of electrification of 0.09 – 0.105 USD/kWh for 24-hour CSP in Uganda in 2040, depending on solar insolation levels.

Transmission costs were obtained through personal communication with Uganda's transmission company UETCL and distribution company UMEME Ltd. On average, 1 km of a 132 kV double circuit line with 70 MVA in Uganda costs 180,000 USD (a number that is similar to figures given by the International Energy Agency [87]), with a significant part of this number independent of the installed capacity due to land right and tower construction costs.

Distribution costs are modelled per grid-electrified person. Following Nerini et al. (2016), the tree-like network structure model by van Ruijven et al. (2012) [64] was used to estimate the required medium-voltage (MV) and low-voltage (LV) line length of the distribution grid per person as well as any fractional substation costs. The resulting costs heavily depend on the population density as lower densities imply higher per person investment requirements to expand the grid. Average costs for the required lines are available from a variety of sources, this paper used the numbers from Mentis et al. (2017) for Africa. Adding these costs in accordance to van Ruijven et al.'s model, and multiplying by the average household size in Uganda gives a value of roughly 1,200 USD per grid-connection per rural household, a similar albeit slightly lower number than what Lenz et al. (2017) have found to be the case for neighbouring Rwanda's grid rollout programme [107]. In terms of off-grid electrification, additional costs (other than module costs) are considered as part of the distribution costs, namely the extra infrastructure investment cost incurred to transport the off-grid to its final household location. In case of larger systems, this can require the building of a new road as well as establishing new distribution channels [81]. It is assumed that these non-module cost are proportional to the log of population density in an area, and are not incurred anymore in urban areas with population densities over 2,000 people. At most, these average additional distribution costs are assumed to be 50% of module costs, while cases of mini-grids in remote areas exist where the non-module cost can exceed module cost [81]. The resulting cost range for the year 2020 of 1300 - 2000 USD for a 250 W off-grid solar home system with battery which is able to provide Tier-3 type electricity is similar to current offerings in the Ugandan market.

B.2 Demand data

Domestic demand in future time periods is assumed to depend on the number of urban and rural people in a geographic cell and the average per capita demand. Rural and urban population sizes are available for all of Uganda's 112 districts from [88]. Future population sizes are estimated by applying a population growth rate (initially matching Uganda's 2016 rate of 3.0% and then slightly decreasing to 2.0% in 2040) to the current population distribution. Furthermore, Uganda's high urbanisation rate of almost 5% in 2016 is factored into the calculation, with the capital city Kampala growing 20% faster than any other city due to Uganda's centralised layout. Urban and rural area size was estimated by matching geospatial population data with Uganda's official urban and rural population data per district to yield population densities for urban and rural areas in each cell. For the latter, a Tier-3 type of electricity demand (which allows to power most home appliances, see [72]) of 160 kWh per person and year in 2040 is assumed for the main demand scenario. This figure is considerably above the average demand for newly connected rural households during their first years of consumption, but considerably below the target demand the Ugandan government has set in its Vision 2040 policy. To study the implications of the per capita demand the government of Uganda officially aims for as part of its Vision 2040, a second, high-demand scenario sets this figure to a Tier-5 type of electricity (which allows to power refrigeration and cooking devices as well as small air conditioning units) demand of 900 kWh per person and year.

No spatially explicit non-household demand data exists in Uganda. To estimate it, as rural businesses are known to consume little electricity compared to urban and semi-urban industrial businesses in East Africa [107], demand is assumed to be directly proportional to the share of the urban population in a cell compared to the national urban population. Hence, most business demand occurs in Kampala and Wakiso, while comparably little demand exists in Northern Uganda, assumptions which are verified by distributor UMEME's dispatch data [71]. In the main demand scenario studied in the paper, the share of business to total demand is assumed to decrease slightly from 77% today to 72 % in 2040 [67]. It should be noted that this constitutes a highly optimistic estimation as commercial demand would almost rise as quickly as household demand, with the latter benefitting from a large increase in new connections. Business demand is assumed to rapidly increase in the high-demand scenario to match the official total per capita electricity consumption target of the Ugandan government in 2040 of roughly 3800 kWh p.c. (i.e. all electricity consumed in Uganda divided by the expected number of people in Uganda in 2040). For the dominating economic hub of Kampala [67, 71], it was assumed that a minimum of 95% of business demand has to be met in 2040.

B.3 Supply data

Data for all existing and several planned power plants as well as transmission and distribution infrastructure are available from Uganda's GIS working group which in 2017 for the first time published comprehensive geospatial data for Uganda's energy system as well as several demographic indicators [68]. Geospatial solar insolation, wind speed, hydro potential, biomass potential and fossil fuel reserves follow from various freely available GIS sources (see Table 2). For potential solar and wind plants, annual geospatial capacity factors as well as generation potentials follow directly from these maps following the calculations laid out by Andrews and Jelley (2017) [78], more general values for average capacity factors were used based on the International Renewable Energy Agency's (IRENA) analyses of African power generation plants (see IRENA references in Table 2) where Ugandan-specific capacity factors were not available. For concentrated solar power, only those districts with easily accessible water resources (like seas or large rivers) were considered due to the cooling requirements of CSP plants. This constitutes a conservative approach as air cooling systems for CSP may become cheaper options of cooling in the coming decades, alleviating the need for water cooling. Detailed geospatial potential on-grid hydropower plant data was taken from [68], while geospatial micro-hydro potential is based on the results calculated be Mentis et al. (2017) for Uganda. Building on a number of Uganda-specific documents on geothermal energy potential and feasibility, the total geothermal potential of 440 MW in Uganda has been divided among the four potential sites in Uganda in accordance to the estimated feasibility at the sites. This has led to an assumption of a potential of 60 MW in Nebbi, 100 MW in Bundibugyo, 130 MW in Hoima, and 150 MW in Kasese district. For biomass generation potential, several sources (see Table 2) indicate that for Uganda, bagasse presents the most promising crops for electricity generation and was thus focused on in the analyses. The potentials were estimated based on global bagasse yield datasets and land as well as irrigation restrictions in Uganda, leading to a total of roughly 500 MW potential spread over 35 districts.

In terms of non-renewables, Uganda currently operates two medium-sized oil-fired plants as the only fossil fuel plants in the country. Uganda is endowed with oil as well as small natural gas reserves which have been discovered in the early 2000s but are yet to be extracted. There are currently no major natural gas or coal imports into Uganda. Recent natural gas discoveries in Tanzania and Mozambique are likely to be used for oversea export and internally, thereby rendering large-scale natural gas or coal-fired power plants unlikely to materialise in Uganda until 2040. As it commonly is more economical to turn coal into electricity close to where the coal is located and transmit it via high-voltage lines rather than shipping the coal to a third country and generate the electricity locally, the model assumes that Uganda has no coal-fired potential until 2040. Natural gas potential is limited to 100 MW in Hoima from its limited domestic resources starting in 2030, as well as relying on imports from neighbouring countries to run 250 MW plants in Hoima and in Tororo. It is furthermore assumed that most of Uganda's oil will be used for export as this is a more economical way than investing in expensive oil-fired power plants. Hence, it is assumed that no additional oil-fired potential exists in Uganda other than potentially keeping the two plants in Tororo and Mukono operational until 2040 (the government plans to close them before this date) [67]. Lastly, Uganda has invested a considerable amount of institutional capacity in building up nuclear energy [92]. While the government's official policy goal is to have 24 GW of nuclear capacity installed by 2040, Uganda's Ministry of Energy takes a more conservative approach and aims to have 2.3 GW of nuclear online during the 2030s [92]. Potential plant locations discussed are Buyende and Lamwo, hence the model used in this paper assigns a theoretical 1.2 GW nuclear potential in these two districts from 2035 each. However, as the model results show, other baseload electrification options such as hydro, geothermal and concentrated solar power are cheaper than nuclear, and no instance of the model under investigation produced a positive nuclear installed capacity for Uganda at any point.

B.4 Transmission and distribution loss data

The long-term timeframe as well as the size of the model prohibit an explicit modelling of voltage drop losses based on Kirchhoff's Second Law due to the inherent numerical complexities arising from non-linearities. As the purpose of the model, rather, is to provide a high-level overview of how the Ugandan power system could look like in 2040, transmission losses are instead modelled as simple percent losses per unit of line length. As virtually all existing transmission lines in Uganda have an operating voltage of 132 kV, this voltage is assumed for newly built lines. The current average transmission losses in Uganda equate to roughly 1.1% per 100 km [71]. For 33 kV distribution lines, an average loss value of 1.8% per 10 km for the Dog conductor was used. For within-cell distribution losses, average per-cell distribution losses for urban and rural areas are calculated by defining a range of within-district distribution losses based on current reported UMEME losses: Distribution losses were roughly 18% on average in 2016, ranging between 5% in some districts and reaching 40% in others [71]. The required average per-person line length requirements as explained in Appendix B1 is then used to place districts on this loss interval using an exponential regression loss function to account for the exponentially increasing losses per added unit of line length. Its minimum appears in the densely-populated capital city Kampala (assumed 5% within district distribution loss) and its maximum appears in rural areas of the sparsely populated Bududa district (assumed 40% loss).

APPENDIX C – OPTIMAL GENERATION CAPACITY BY DISTRICT

Table A: Optimal installed capacity in MW for forcing no equality (NE) and full equality (FE) of regional and urban versus rural electrification for all 112 districts in Uganda

	Fossil		**Hydro**		**Geoth.**		**Biomass**		**Solar PV**		**CSP**		**Wind**		**Off-grid**		**Total**	
District	NE	FE	NE	FE	NE	FE	NE	FE	NE	FE	NE	FE	NE	FE	NE	FE	NE	FE
Abim	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	10	2	10
Adjumani	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	21	5	21
Agago	0	0	0	0	0	0	10	10	0	0	0	0	0	0	3	21	13	31
Alebtong	0	0	0	0	0	0	5	5	0	0	0	0	0	0	26	21	31	26
Amolatar	0	0	0	0	0	0	0	0	0	0	0	0	0	0	19	15	19	15
Amudat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	10	13	10
Amuria	0	0	0	0	0	0	8	8	0	0	0	0	0	0	2	25	10	33
Amuru	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	17	1	17
Apac	0	0	0	0	0	0	9	9	0	0	50	50	0	0	41	33	100	92
Arua	0	0	11	11	0	0	0	0	0	0	0	0	0	0	81	64	92	75
Budaka	0	0	0	0	0	0	1	1	0	0	0	0	0	0	23	19	24	20
Bududa	0	0	0	0	0	0	0	0	78	78	0	0	0	0	21	6	99	84
Bugiri	0	0	0	0	0	0	3	3	0	0	0	0	0	0	43	35	46	38
Buhweju	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	12	1	12
Buikwe	0	0	0	0	0	0	10	10	0	0	500	500	0	0	48	35	558	545
Bukedea	0	0	0	0	0	0	3	3	0	0	0	0	0	0	21	17	24	20
Bukomansimbi	0	0	0	0	0	0	2	2	0	0	0	0	0	0	18	15	20	17
Bukwo	0	0	15	15	0	0	0	0	0	0	0	0	0	0	9	7	24	22
Bulambuli	0	0	7	7	0	0	0	0	79	199	0	0	0	0	18	14	104	220
Buliisa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13	11	13	11
Bundibugyo	0	0	5	5	100	100	0	0	0	0	0	0	0	0	24	18	129	123
Bushenyi	0	0	1	1	0	0	0	0	0	0	0	0	0	0	28	23	29	24
Busia	0	0	0	0	0	0	0	0	0	0	0	0	0	0	36	27	36	27
Butaleja	0	0	0	0	0	0	2	2	0	0	0	0	0	0	27	22	29	24
Butambala	0	0	0	0	0	0	1	1	0	0	0	0	0	0	2	10	3	11
Buvuma	0	0	0	0	0	0	0	0	0	0	0	0	0	0	11	9	11	9
Buyende	0	0	0	0	0	0	0	0	0	0	108	84	0	0	38	31	146	115
Dokolo	0	0	0	0	0	0	0	0	0	0	0	0	0	0	20	16	20	16
Gomba	0	0	0	0	0	0	5	5	0	0	0	0	0	0	2	16	7	21
Gulu	0	0	0	0	0	0	10	10	0	0	0	0	0	0	45	31	55	41
Hoima	350	350	24	24	130	130	0	0	0	0	0	0	0	0	63	52	567	556
Ibanda	0	0	3	3	0	0	0	0	0	0	0	0	0	0	8	26	11	29
Iganga	0	0	0	0	0	0	3	3	0	0	0	0	0	0	54	41	57	44
Isingiro	0	0	41	41	0	0	0	0	0	0	0	0	0	0	7	49	48	90
Jinja	0	0	778	778	0	0	53	53	0	0	0	0	0	0	43	30	874	861
Kaabong	0	0	0	0	0	0	0	0	43	24	0	0	69	69	18	15	130	108
Kabale	0	0	0	0	0	0	0	0	0	0	0	0	0	0	59	48	59	48
Kabarole	0	0	12	12	0	0	0	0	0	0	0	0	0	0	52	44	64	56
Kaberamaido	0	0	0	0	0	0	5	5	0	0	50	50	0	0	24	19	79	74
Kalangala	0	0	0	0	0	0	2	2	0	0	0	0	0	0	7	6	9	8
Kaliro	0	0	0	0	0	0	12	12	0	0	0	0	0	0	26	21	38	33
Kalungu	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	18	14	18
Kampala	0	0	0	0	0	0	0	0	0	0	0	0	0	0	118	94	118	94
Kamuli	0	0	0	0	0	0	5	5	0	0	0	0	0	0	53	42	58	47
Kamwenge	0	0	18	18	0	0	0	0	0	0	0	0	0	0	3	41	21	59
Kanungu	0	0	13	13	0	0	0	0	0	0	0	0	0	0	7	26	20	39
Kapchorwa	0	0	4	4	0	0	0	0	23	23	0	0	0	0	11	8	38	35
Kasese	0	0	61	61	150	150	0	0	398	382	353	241	0	0	71	53	1033	887
Katakwi	0	0	0	0	0	0	7	7	10	0	0	0	0	0	17	14	34	21
Kayunga	0	0	0	0	0	0	5	5	0	0	500	500	0	0	41	33	546	538
Kibaale	0	0	51	51	0	0	13	13	0	0	0	0	0	0	6	76	70	140
Kiboga	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	15	4	15
Kibuku	0	0	0	0	0	0	1	1	0	0	0	0	0	0	22	18	23	19

Kiruhura	0	0	0	0	0	0	14	14	0	0	0	0	0	0	3	32	17	46
Kiryandongo	0	0	698	698	0	0	10	10	0	0	0	0	0	0	30	25	738	733
Kisoro	0	0	0	2	0	0	0	0	0	0	0	0	0	0	32	25	32	27
Kitgum	0	0	0	0	0	0	0	0	0	0	0	0	1	1	5	19	6	20
Koboko	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	5	4	5
Kole	0	0	0	0	0	0	3	3	0	0	0	0	0	0	27	21	30	24
Kotido	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	17	3	17
Kumi	0	0	0	0	0	0	0	0	247	161	0	0	0	0	26	21	273	182
Kween	0	0	20	20	0	0	0	0	0	0	0	0	0	0	10	8	30	28
Kyankwanzi	0	0	0	0	0	0	7	7	0	0	0	0	0	0	26	19	33	26
Kyegegwa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	29	5	29
Kyenjojo	0	0	0	0	0	0	7	7	0	0	0	0	0	0	8	42	15	49
Lamwo	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	14	4	14
Lira	0	0	0	0	0	0	4	4	0	0	0	0	0	0	42	31	46	35
Luuka	0	0	0	0	0	0	2	2	0	0	0	0	0	0	27	21	29	23
Luwero	0	0	0	0	0	0	7	7	0	0	0	0	0	0	46	39	53	46
Lwengo	0	0	0	0	0	0	3	3	0	0	0	0	0	0	32	26	35	29
Lyantonde	0	0	0	0	0	0	3	3	0	0	0	0	0	0	2	9	5	12
Manafwa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	39	23	39	23
Maracha	0	0	0	0	0	0	0	0	0	0	0	0	0	0	22	17	22	17
Masaka	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	25	17	25
Masindi	0	0	350	350	0	0	26	26	0	0	0	0	0	0	11	28	387	404
Mayuge	0	0	0	0	0	0	2	2	0	0	500	500	0	0	52	33	554	535
Mbale	0	0	0	0	0	0	0	0	0	0	0	0	0	0	50	23	50	23
Mbarara	0	0	0	0	0	0	0	0	0	0	0	0	0	0	25	40	25	40
Mitooma	0	0	3	3	0	0	0	0	0	0	0	0	0	0	23	18	26	21
Mityana	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	31	5	31
Moroto	0	0	0	0	0	0	0	0	0	0	0	0	70	70	12	9	82	79
Moyo	0	0	7	7	0	0	0	0	0	0	0	0	0	0	1	12	8	19
Mpigi	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	25	6	25
Mubende	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	66	5	66
Mukono	49	49	0	0	0	0	0	0	0	0	310	310	0	0	65	47	424	406
Nakapiripirit	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18	14	18	14
Nakaseke	0	0	0	0	0	0	11	11	0	0	0	0	0	0	8	20	19	31
Nakasongola	0	0	0	0	0	0	11	11	0	0	159	226	0	0	3	16	173	253
Namayingo	0	0	0	0	0	0	0	0	0	0	138	101	0	0	25	20	163	121
Namutumba	0	0	0	0	0	0	3	3	0	0	0	0	0	0	28	23	31	26
Napak	0	0	0	0	0	0	0	0	38	31	0	0	0	0	3	13	41	44
Nebbi	0	0	0	0	60	60	0	0	0	0	0	0	0	0	41	31	101	91
Ngora	0	0	0	0	0	0	2	2	112	112	0	0	0	0	14	12	128	126
Ntoroko	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	7	3	7
Ntungamo	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	48	7	48
Nwoya	0	0	844	844	0	0	0	0	0	0	0	0	0	0	2	12	846	856
Otuke	0	0	0	0	0	0	5	5	0	0	0	0	0	0	1	10	6	15
Oyam	0	0	0	0	0	0	7	7	0	0	0	0	0	0	43	35	50	42
Pader	0	0	112	112	0	0	0	0	0	0	0	0	0	0	2	16	114	128
Pallisa	0	0	0	0	0	0	0	0	0	0	0	0	0	0	43	35	43	35
Rakai	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	50	3	50
Rubirizi	0	0	8	8	0	0	0	0	0	0	0	0	0	0	15	12	23	20
Rukungiri	0	0	0	0	0	0	0	0	0	0	0	0	0	0	39	31	39	31
Serere	0	0	0	0	0	0	0	0	0	0	0	0	0	0	31	25	31	25
Sheema	0	0	0	0	0	0	0	0	0	0	0	0	0	0	26	22	26	22
Sironko	0	0	0	0	0	0	0	0	113	113	0	0	0	0	25	19	138	132
Soroti	0	0	0	0	0	0	4	4	0	0	0	0	0	0	31	23	35	27
Ssembabule	0	0	0	0	0	0	8	8	0	0	0	0	0	0	2	25	10	33
Tororo	336	336	0	0	0	0	4	4	0	0	0	0	0	0	58	46	398	386
Wakiso	0	0	0	0	0	0	0	0	0	0	0	0	0	0	65	44	65	44
Yumbe	0	0	20	20	0	0	0	0	0	0	0	0	0	0	53	34	73	54
Zombo	0	0	4	4	0	0	0	0	0	0	0	0	0	0	24	18	28	22
Total	**735**	**735**	**3110**	**3112**	**440**	**440**	**316**	**316**	**1142**	**1124**	**2668**	**2561**	**141**	**141**	**2642**	**2863**	**11193**	**11292**

REFERENCES

[1] World Bank. World Development Indicators. Washington, DC: World Bank; 2018.

[2] Trotter PA, McManus MC, Maconachie R. Electricity planning and implementation in sub-Saharan Africa: A systematic review. Renewable and Sustainable Energy Reviews. 2017;74:1189-209.

[3] Wang X, McDonald JR. Modern power system planning: McGraw-Hill Companies; 1994.

[4] Koltsaklis NE, Dagoumas AS, Kopanos GM, Pistikopoulos EN, Georgiadis MC. A spatial multi-period long-term energy planning model: a case study of the Greek power system. Applied Energy. 2014;115:456-82.

[5] Zhu J, Chow M-y. A review of emerging techniques on generation expansion planning. Ieee T Power Syst. 1997;12:1722-8.

[6] Koltsaklis NE, Dagoumas AS. State-of-the-art generation expansion planning: A review. Applied Energy. 2018;230:563-89.

[7] Latorre G, Cruz RD, Areiza JM, Villegas A. Classification of publications and models on transmission expansion planning. Ieee T Power Syst. 2003;18:938-46.

[8] Lumbreras S, Ramos A. The new challenges to transmission expansion planning. Survey of recent practice and literature review. Electric Power Systems Research. 2016;134:19-29.

[9] Hemmati R, Hooshmand R-A, Khodabakhshian A. Comprehensive review of generation and transmission expansion planning. IET Generation, Transmission & Distribution. 2013;7:955-64.

[10] Yuan J, Xu Y, Kang J, Zhang X, Hu Z. Nonlinear integrated resource strategic planning model and case study in China's power sector planning. Energy. 2014;67:27-40.

[11] Hemmati R, Saboori H, Jirdehi MA. Multistage generation expansion planning incorporating large scale energy storage systems and environmental pollution. Renewable Energy. 2016;97:636-45.

[12] Modiri-Delshad M, Kaboli SHA, Taslimi-Renani E, Rahim NA. Backtracking search algorithm for solving economic dispatch problems with valve-point effects and multiple fuel options. Energy. 2016;116:637-49.

[13] Sebtahmadi SS, Azad HB, Kaboli SHA, Islam MD, Mekhilef S. A PSO-DQ current control scheme for performance enhancement of Z-source matrix converter to drive IM Fed by abnormal voltage. IEEE Transactions on Power Electronics. 2018;33:1666-81.

[14] Kaboli SHA, Selvaraj J, Rahim NA. Long-term electric energy consumption forecasting via artificial cooperative search algorithm. Energy. 2016;115:857-71.

[15] Kaboli SHA, Selvaraj J, Rahim NA. Rain-fall optimization algorithm: A population based algorithm for solving constrained optimization problems. Journal of Computational Science. 2017;19:31-42.

[16] Zhang N, Hu Z, Shen B, He G, Zheng Y. An integrated source-grid-load planning model at the macro level: Case study for China's power sector. Energy. 2017;126:231-46.

[17] Rider MJ, Garcia AV, Romero R. Power system transmission network expansion planning using AC model. IET Generation, Transmission & Distribution. 2007;1:731-42.

[18] Thangavelu SR, Khambadkone AM, Karimi IA. Long-term optimal energy mix planning towards high energy security and low GHG emission. Applied energy. 2015;154:959-69.

[19] Guo Z, Cheng R, Xu Z, Liu P, Wang Z, Li Z, et al. A multi-region load dispatch model for the long-term optimum planning of China’s electricity sector. Applied energy. 2017;185:556-72.

[20] Pozo D, Sauma EE, Contreras J. A three-level static MILP model for generation and transmission expansion planning. Ieee T Power Syst. 2013;28:202-10.

[21] Alizadeh B, Jadid S. Reliability constrained coordination of generation and transmission expansion planning in power systems using mixed integer programming. IET generation, transmission & distribution. 2011;5:948-60.

[22] Dong C, Huang GH, Cai YP, Xu Y. An interval-parameter minimax regret programming approach for power management systems planning under uncertainty. Applied Energy. 2011;88:2835-45.

[23] Bakirtzis GA, Biskas PN, Chatziathanasiou V. Generation expansion planning by MILP considering mid-term scheduling decisions. Electric Power Systems Research. 2012;86:98-112.

[24] Kannan S, Slochanal SMR, Padhy NP. Application and comparison of metaheuristic techniques to generation expansion planning problem. Ieee T Power Syst. 2005;20:466-75.

[25] Park YM, Park JB, Won JR. A hybrid genetic algorithm/dynamic programming approach to optimal long-term generation expansion planning. International Journal of Electrical Power & Energy Systems. 1998;20:295-303.

[26] Yildirim M, Erkan K, Ozturk S. Power generation expansion planning with adaptive simulated annealing genetic algorithm. Int J Energ Res. 2006;30:1188-99.

[27] Shayeghi H, Mahdavi M, Bagheri A. Discrete PSO algorithm based optimization of transmission lines loading in TNEP problem. Energy Conversion and management. 2010;51:112-21.

[28] Aghaei J, Amjady N, Baharvandi A, Akbari M-A. Generation and transmission expansion planning: MILP–based probabilistic model. Ieee T Power Syst. 2014;29:1592-601.

[29] Cai YP, Huang GH, Tan Q, Yang ZF. An integrated approach for climate-change impact analysis and adaptation planning under multi-level uncertainties. Part I: Methodology. Renewable and Sustainable Energy Reviews. 2011;15:2779-90.

[30] Chen H, Tang B-J, Liao H, Wei Y-M. A multi-period power generation planning model incorporating the non-carbon external costs: A case study of China. Applied energy. 2016;183:1333-45.

[31] Guerra OJ, Tejada DA, Reklaitis GV. An optimization framework for the integrated planning of generation and transmission expansion in interconnected power systems. Applied Energy. 2016;170:1-21.

[32] Georgiou PN. A bottom-up optimization model for the long-term energy planning of the Greek power supply sector integrating mainland and insular electric systems. Computers & Operations Research. 2016;66:292-312.

[33] Sharan I, Balasubramanian R. Integrated generation and transmission expansion planning including power and fuel transportation constraints. Energy Policy. 2012;43:275-84.

[34] Maghouli P, Hosseini SH, Buygi MO, Shahidehpour M. A multi-objective framework for transmission expansion planning in deregulated environments. Ieee T Power Syst. 2009;24:1051-61.

[35] Zhang Q, McLellan BC, Tezuka T, Ishihara KN. An integrated model for long-term power generation planning toward future smart electricity systems. Applied Energy. 2013;112:1424-37.

[36] Ren H, Zhou W, Nakagami Ki, Gao W, Wu Q. Multi-objective optimization for the operation of distributed energy systems considering economic and environmental aspects. Applied Energy. 2010;87:3642-51.

[37] Luz T, Moura P, de Almeida A. Multi-objective power generation expansion planning with high penetration of renewables. Renewable and Sustainable Energy Reviews. 2017.

[38] Linares P, Romero C. A multiple criteria decision making approach for electricity planning in Spain: economic versus environmental objectives. Journal of the Operational Research Society. 2000;51:736-43.

[39] Muis ZA, Hashim H, Manan ZA, Taha FM, Douglas PL. Optimal planning of renewable energy-integrated electricity generation schemes with CO2 reduction target. Renewable energy. 2010;35:2562-70.

[40] Antunes CH, Martins AG, Brito IS. A multiple objective mixed integer linear programming model for power generation expansion planning. Energy. 2004;29:613-27.

[41] Meza JLC, Yildirim MB, Masud ASM. A multiobjective evolutionary programming algorithm and its applications to power generation expansion planning. IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans. 2009;39:1086-96.

[42] Meza JLC, Yildirim MB, Masud ASM. A model for the multiperiod multiobjective power generation expansion problem. Ieee T Power Syst. 2007;22:871-8.

[43] Unsihuay-Vila C, Marangon-Lima JW, De Souza ACZ, Perez-Arriaga IJ. Multistage expansion planning of generation and interconnections with sustainable energy development criteria: A multiobjective model. International Journal of Electrical Power & Energy Systems. 2011;33:258-70.

[44] Trotter PA, Maconachie R, McManus MC. The impact of political objectives on optimal electricity generation and transmission in the Southern African Power Pool. J Energy South Afr. 2017;28:27-42.

[45] Trotter PA, Maconachie R, McManus MC. Solar energy's potential to mitigate political risks: The case of an optimised Africa-wide network. Energy Policy. 2018;117:108-26.

[46] Marler RT, Arora JS. Survey of multi-objective optimization methods for engineering. Structural and multidisciplinary optimization. 2004;26:369-95.

[47] Moeini-Aghtaie M, Abbaspour A, Fotuhi-Firuzabad M. Incorporating large-scale distant wind farms in probabilistic transmission expansion planning—Part I: Theory and algorithm. Ieee T Power Syst. 2012;27:1585-93.

[48] Trotter PA, Maconachie R. Populism, post-truth politics and the failure to deceive the public in Uganda's energy debate. Energy Research & Social Science. 2018.

[49] Russo D, Miketa A. Benefits, Challenges, and Analytical Approaches to Scaling Up Renewables Through Regional Planning and Coordination of Power Systems in Africa. Current Sustainable/Renewable Energy Reports. 2019:1-8.

[50] Trotter PA. Rural electrification, electrification inequality and democratic institutions in sub-Saharan Africa. Energy for Sustainable Development. 2016;34:111-29.

[51] Pérez-Fortes M, Laínez-Aguirre JM, Arranz-Piera P, Velo E, Puigjaner L. Design of regional and sustainable bio-based networks for electricity generation using a multi-objective MILP approach. Energy. 2012;44:79-95.

[52] Arndt C, Davies R, Gabriel S, Makrelov K, Merven B, Hartley F, et al. A sequential approach to integrated energy modeling in South Africa. Applied Energy. 2016;161:591-9.

[53] Beck J, Kempener R, Cohen B, Petrie J. A complex systems approach to planning, optimization and decision making for energy networks. Energy Policy. 2008;36:2803-13.

[54] Nhete TD. Electricity sector reform in Mozambique: a projection into the poverty and social impacts. J Clean Prod. 2007;15:190-202.

[55] Mahapatra S, Dasappa S. Rural electrification: Optimising the choice between decentralised renewable energy sources and grid extension. Energy for Sustainable Development. 2012;16:146-54.

[56] Zvoleff A, Kocaman AS, Huh WT, Modi V. The impact of geography on energy infrastructure costs. Energy Policy. 2009;37:4066-78.

[57] Parshall L, Pillai D, Mohan S, Sanoh A, Modi V. National electricity planning in settings with low pre-existing grid coverage: Development of a spatial model and case study of Kenya. Energy Policy. 2009;37:2395-410.

[58] Moner-Girona M, Bódis K, Huld T, Kougias I, Szabó S. Universal access to electricity in Burkina Faso: scaling-up renewable energy technologies. Environmental Research Letters. 2016;11:084010.

[59] Sanoh A, Parshall L, Sarr OF, Kum S, Modi V. Local and Rational electricity planning in Senegal: Scenarios and policies. Energy for Sustainable Development. 2012;16:13-25.

[60] Szabo S, Bódis K, Huld T, Moner-Girona M. Energy solutions in rural Africa: mapping electrification costs of distributed solar and diesel generation versus grid extension. Environmental Research Letters. 2011;6:034002.

[61] Mentis D, Howells M, Rogner H, Korkovelos A, Arderne C, Zepeda E, et al. Lighting the World: the first application of an open source, spatial electrification tool (OnSSET) on Sub-Saharan Africa. Environmental Research Letters. 2017;12:085003.

[62] Ohiare S. Expanding electricity access to all in Nigeria: a spatial planning and cost analysis. Energy, Sustainability and Society. 2015;5.

[63] Kemausuor F, Adkins E, Adu-Poku I, Brew-Hammond A, Modi V. Electrification planning using Network Planner tool: The case of Ghana. Energy for Sustainable Development. 2014;19:92-101.

[64] Van Ruijven BJ, Schers J, van Vuuren DP. Model-based scenarios for rural electrification in developing countries. Energy. 2012;38:386-97.

[65] Milano F. An open source power system analysis toolbox. Ieee T Power Syst. 2005;20:1199-206.

[66] Afolabi OA, Ali WH, Cofie P, Fuller J, Obiomon P, Kolawole ES. Analysis of the load flow problem in power system planning studies. Energy and Power Engineering. 2015;7:509.

[67] Electricity Regulatory Authority. The Least Cost Generation Plan - 2016 - 2025. Kampala, Uganda2016.

[68] Energy Sector GIS Working Group Uganda. Uganda Energy Sector GIS datasets. http://data-energy-gis.opendata.arcgis.com/2018.

[69] UMEME. Integrated Annual Report 2016. Kampala, Uganda2017.

[70] Government of Uganda. Uganda Vision 2040. Kampala, Uganda2015.

[71] UMEME. Uganda energy dispatch data. In: UETCL UL, editor. Personal communication with UMEME2017.

[72] Nerini FF, Broad O, Mentis D, Welsch M, Bazilian M, Howells M. A cost comparison of technology approaches for improving access to electricity services. Energy. 2016;95:255-65.

[73] IEA. Trends in Photovoltaic Applications 2016. Photovoltaic Power Systems Programme. Paris, France: IEA; 2016.

[74] International Renewable Energy Agency. Africa Power Sector - Planning and Prospects for Renewable Energy. Abu Dhabi, UAE: International Renewable Energy Agency; 2015.

[75] International Renewable Energy Agency. Africa 2030: Roadmap for a Renewable Energy Future. Abu Dhabi, UAE: International Renewable Energy Agency; 2015.

[76] International Renewable Energy Agency. Prospects for the African Power Sector - Scenarios and Strategies for Africa Project. Abu Dhabi, UAE: International Renewable Energy Agency; 2012.

[77] Trotter PA. Discussion paper: Identifying and resolving methodological issues in previous Africa-wide electricity planning optimisation research-A comment on Sanoh et al.(2014). Renewable Energy. 2017.

[78] Andrews J, Jelley N. Energy science: principles, technologies, and impacts: Oxford university press; 2017.

[79] World Bank. Technical and economic assessment of off-grid, mini-grid and grid electrification technologies - Annex 1. Washington, DC: World Bank Group; 2005.

[80] National Power Training Institute. Capital Cost Benchmarks for Distribution Business. Faridabad, India: NPTI; 2014.

[81] Wrigley N. The Economics of RE off-grid projects in Africa and the Multi-Utility Concept as a Future Opportunity. Practical Challenges of Sustainable Electrification in Africa. Oxford, UK: Smith School of Enterprise and the Environment; 2018.

[82] Parties of the 2015 United Nations Climate Change Conference. Individual Country Intended Nationally Determined Contributions (INDCs). http://www4.unfccc.int/Submissions/INDC/Submission%20Pages/submissions.aspx: United Nations Framework Convention on Climate Change; 2015.

[83] International Renewable Energy Agency. Renewable Power Generation Costs in 2017. Abu Dhabi, UAE: IRENA; 2018.

[84] World Nuclear Association. Comparison of Lifecycle Greenhouse Gas Emissions of Various Electricity Generation Sources. London, UK: WNA; 2011.

[85] Burkhardt JJ, Heath G, Cohen E. Life cycle greenhouse gas emissions of trough and tower concentrating solar power electricity generation. Journal of Industrial Ecology. 2012;16:S93-S109.

[86] Government of Uganda - Office of the Auditor General. Implementation of transmission line infrastructure projects. Value for Money Audit Report Series. Kampala, Uganda: OAG; 2015.

[87] International Energy Agency. Electricity Transmission and Distribution. IEA ETSAP - Technology Brief E12. 2014.

[88] Uganda Bureau of Statistics. National Population and Housing Census 2014 - Main Report. Kampala, Uganda2016.

[89] World Bank. The Growth Challenge: Can Ugandan Cities get to Work? Uganda Economic Update 5th Edition. Washington, DC2015.

[90] Huld T, Müller R, Gambardella A. A new solar radiation database for estimating PV performance in Europe and Africa. Solar Energy. 2012;86:1803-15.

[91] International Renewable Energy Agency. Global Atlas for Renewable Energy. Abu Dhabi, UAE.: International Renewable Energy Agency; 2017.

[92] Isingoma JB. Status of the Uganda Nuclear Power Programme. Technical Meeting on Topical Issues in the Development of Nuclear Power Infrastructure. Vienna, Austria2017.

[93] International Atomic Energy Agency. Analysis of Infrastructure for Renewable Power in - Eastern and Southern Africa. Abu Dhabi, UAE: IRENA; 2015.

[94] Uganda Ministry of Energy and Mineral Development. Biomass Energy Strategy (BEST) Uganda. Kampala, Uganda2015.

[95] Food and Agriculture Organization of the United Nations. Global Agro-Ecological Zones - Sugarcane dataset. http://www.fao.org/nr/gaez/en/2018.

[96] Rabelo SC, Carrere H, Maciel Filho R, Costa AC. Production of bioethanol, methane and heat from sugarcane bagasse in a biorefinery concept. Bioresource technology. 2011;102:7887-95.

[97] Purchase BS, Rosettenstein S, Bezuidenhoudt DV. Challenges and potential solutions for storage of large quantities of bagasse for power generation. Intern Sugar J. 2014;116:592-602.

[98] Macknick J, Newmark R, Heath G, Hallett KC. Operational water consumption and withdrawal factors for electricity generating technologies: a review of existing literature. Environmental Research Letters. 2012;7:045802.

[99] Nile Basin Initiative. State of the River Nile Basin 2012 - Ch. 6: Hydropower Potential and the Region's Rising Energy Demand. Entebbe, Uganda: Nile Basin Initiative; 2013.

[100] Management Innovations Uganda. Report on Value Chain Analysis of Iron and Steel Uganda. Kampala, Uganda: Ministry of Works and Transport Uganda; 2015.

[101] Uganda Bureau of Statistics. 2014 Statistical Abstract. Kampala, Uganda: UBOS; 2014.

[102] Central Intelligence Agency. The World Factbook. Washington, DC: Central Intelligence Agency; 2016.

[103] Uganda Go. Rural Electrification Strategy and Plan Covering the Period 2013-2022. Kampala: Ministery of Energy and Mineral Development; 2012.

[104] Ma S, Urpelainen J. Distributed power generation in national rural electrification plans: An international and comparative evaluation. Energy Research & Social Science. 2018;44:1-5.

[105] KfW. GET FiT Uganda - Annual Report 2016. Kampala, Uganda: KfW; 2017.

[106] Dreyfus SE. An appraisal of some shortest-path algorithms. Operations research. 1969;17:395-412.

[107] Lenz L, Munyehirwe A, Peters J, Sievert M. Does large-scale infrastructure investment alleviate poverty? Impacts of Rwanda's electricity access roll-out program. World Development. 2017;89:88-110.