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Mid- to long-term capacity planning for a reliable power system in Kenya

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ABSTRACT

Over the coming decades, Kenya is likely to see a large increase in electricity demand driven by economic growth and wider electrification of different sectors. At the same time, Kenya remains committed to maintain its high share of renewable generation. This study proposes a novel framework to soft link OSeMOSYS, a capacity expansion model (CEM), and FlexTool, a production cost model (PCM), to address the limitations of CEMs in the representation of variable renewable energy sources. Results show the effectiveness of the methodology in identifying critical grid issues that would have been missed by the capacity expansion model alone, especially in the case of a higher penetration of non-dispatchable sources. They also confirm that based on robust planning approaches, Kenya is well placed to maintain its very low carbon generation system under different demand growth projections, leveraging on firm generation from geothermal and high wind potential.

1. Introduction

1.1. Kenyan context

The Kenyan electricity system has undergone a significant transformation over the last decade, more than doubling access to electricity to over 75% of the population [1], up from 36% just 10 years ago. This increase in access and therefore demand for electricity has been provided mainly by an expansion in renewable generation capacity, notably from geothermal and wind. In 2021, over 85% of electricity generated came from renewable sources, an increase on a 75% share a decade before. This progress in expanding access whilst maintaining a very high share of renewable generation shows the potential of serving increasing energy demands whilst doing so with clean energy and contributing to meeting the country's Nationally Determined Contribution (NDC) [2].

However, Kenya is likely to see further high increases in demand for electricity over the coming decades, resulting from economic growth and the wider electrification of different economic sectors. At the same time, at the political level, Kenya remains committed to maintaining its high share of renewable generation, with a target to hit 100% renewable energy by 2030 [3]. The projected demand growth combined with the need to have a fully renewable system by 2030 and beyond brings a number of potential challenges to ensuring new investment but also for system operation, such as low inertia in the system; transmission constraints leading to load shedding, out-of-merit thermal dispatch; low off-peak demand and high must-run capacity resulting in energy curtailment.

The Kenyan government is actively looking to understand and assess these challenges via their planning process, both in the short term (via the Medium-Term Plan – MTP [4]) and longer term (via the Least Cost Power Development Plan – LCPDP [5,6]), through a process started in 2016 with the publication of the Power Generation and Transmission Master Plan [4,5]. The latest version of the long-term report highlights the need for a comprehensive study on additional grid requirements for the envisioned increased levels of intermittent renewable energy sources, suggesting looking into storage solutions such as battery energy systems and pumped hydropower. To do this, the government are using

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Acronyms and abbreviations

CEM	Capacity Expansion Models
COD	Commercial Operation Date
HD	High Demand
INEP	Integrated National Energy Plan
IRENA	International Renewable Energy Agency
LCPDP	Least Cost Power Development Plan
LCR	Low-Cost Renewables
LMIC	Low- and Middle-Income Country
MTP	Medium-Term Plan
PCM	Production Cost Model
REF	Reference
RoCoF	Rate of Change of Frequency
SDGs	Sustainable Development Goals
SSA	Sub-Saharan Africa
UN	United Nations
VRE	Variable Renewable Energy

Models

Antares	–
COPPER	Canadian Opportunities for Planning and Production of Electricity Resources
Dispa-SET	–
LEAP	Low Emissions Analysis Platform
NEMO	Next Energy Modelling system for Optimisation
OnSSET	Open-Source Spatial Electrification Tool
OSeMOSYS	Open-Source energy MOdelling SYStem
PLEXOS	–
SILVER	Strategic Integration of Large-capacity Variable Energy Resources
SPLAT	System Planning Test
SWITCH	Solar and Wind energy Integrated with Transmission and Conventional sources
TEMBA	The Electricity Model Base for Africa
TIMES	The Integrated MARKAL-EFOM System

a range of modelling tools to inform the planning process. In this paper, we present a novel model linking analysis used by the planning team, using OSeMOSYS and FlexTool, to assess how Kenya can meet its growing demand whilst retaining its objective of a fully renewable system.

The structure of the paper is as follows; in section 1.2, we first review the literature on modelling studies to date, to determine the novelty and suitability of our proposed approach set out in section 2. Section 3 outlines the scenarios used in the study. Results are presented in section 4, with the discussion and conclusions provided in sections 5 and 6 respectively.

1.2. Literature review

In recent years, a growing body of literature has focused on energy system planning in Low- and Middle-Income Countries (LMICs). Common trends and approaches are identified by a number of articles that have reviewed the topic focusing on different geographical areas [7,8] or aspects of planning [9–11].

An early review by Trotter et al. [7] identifies adequate policy design, sufficient finance, favourable political conditions and local capacity building as key success factors for the electrification in sub-Saharan Africa (SSA). The need for capacity building is also highlighted by Musonye et al. [8], with European-based institutions often found to be the main authors of energy modelling studies in the SSA region. In parallel to a wider participation of local stakeholders to the modelling process, a better representation of key system requirements such as spinning reserve, ramping rates, system inertia, peak loads, and quick start reserve margins are identified as needed to make modelling more realistic.

Concerning specific planning aspects, a recurring topic of focus is the electrification of rural areas. The role of large-scale planning tools has been reviewed by Ciller and Lumbreras [9], considering techniques, software tools and approaches to evaluate grid extension and the diffusion of mini-grids and stand-alone systems. They propose a classification of models based on complexity and computation speed, and identify areas for future development, like the introduction of multi-objective optimisation. There is also a focus in the literature on how to best include variable renewable energy (VRE) sources in the planning process [10,11]. Das et al. [10] have analysed this from a methodological point of view, distinguishing between exogenous and endogenous approaches. Exogenous methods are characterized by a variety of methodologies that are differentiated by distinguishing between unidirectional or bidirectional links, and soft- or hard-linking. Endogenous approaches avoid the need for complex data transfer procedures yet require a careful calibration of the model itself and might be subject to structural limitations in the representation the variability of renewable sources. The focus of Sterl's review [11] is on the actual study findings in the literature, rather than on their methodological approaches. The model-based literature suggests that key elements for the integration of VRE sources in the African continent are increased interconnections between power pools, the capacity of exploiting spatio-temporal complementarities between solar PV, wind and hydropower, and large-scale deployment of energy storage.

1.2.1. Modelling the variability of renewable energy sources

The main issue with increasing the share of VRE sources in power system planning is how to correctly estimate flexibility requirements [10,12]. Numerous Capacity Expansion Models (CEMs) exist and have been analysed and categorized from multiple perspectives in different review articles [12–14]. Examples of CEMs include TIMES [15], OSeMOSYS [16], and LEAP [17]. Yet most CEMs have an embedded limited capability of representing flexibility because of the simplifications introduced in the formulation of the problem, especially with regard to the use of timeslices [18]. The process of averaging time series to define loads and VRE generation per timeslice leads to an underestimation of variability and inadequate expression of the chronological order of timesteps. Moreover, as shown by Merrick et al. [19], if 10 timeslices are sufficient to capture variability in a traditional power system, the introduction of VRE can increase that number by up to 1000. Operational constraints of power systems are also difficult to implement because of low temporal resolution and missing chronology between timeslices [20].

Production Cost Models (PCMs), on the other hand, are intended for validation of the technical feasibility of a given system, typically by minimising the operation costs for given capacities [18]. Likewise with CEMs, they provide the generation dispatch of power plants through cost optimisation. However, their results are more accurate at a finer time resolution, usually at an hourly level, and take into account various reliability constraints that are not included in CEMs. Because of this detailed modelling, they do not provide details on the expansion of the grid which would be too complex for the optimisation. Examples of PCMs include PLEXOS [21], Antares [22], Dispa-Set [23] and FlexTool [24,25].

Multiple approaches have been proposed in the literature to solve the shortcomings in flexibility requirements estimation, and some reviews have been published on the topic [10,12,14,26]. From a user perspective, capacity expansion planning studies require either (a) to adapt

CEMs to improve how flexibility is accounted for, (b) linking of CEMs to PCMs, or (c) use of models that integrate both investment planning and unit commitment.

1.2.2. Soft linking between power system planning and operation models

The approach adopted in this study is a bidirectional soft-linking of a capacity expansion model and a production cost model. Soft linking is a practice that involves transfer of information from one model to another, controlled by the user [27], a terminology derived from studies linking economic and energy models from mid-1990s. This contrast to hard linking approaches, which simultaneously solves interconnected models without user intervention.

An increasing number of works in the literature have considered soft-linking approaches between power system planning models and operation ones. For example, TIMES and PLEXOS models were linked to analyse the 2020 Irish power system back in 2012 [28]. Results show that, due to the lower temporal resolution and missing technical constraints, the long-term planning model undervalues flexibility requirements and wind curtailment, while it overestimates the role of baseload technologies. A similar procedure is outlined by Deane et al. [29], where a six-region TIMES model of Italy is linked to a model of the Italian power system in PLEXOS. Findings identify the increasing need for flexibility with increasing VRE share and concerns on the capability of the Italian energy system to provide adequate supply. More recently, Alimou et al. [22] assessed the security of supply of the French power generation sector for the period 2013 to 2050, while developing a more general methodological framework based on a multi-model approach. The TIMES model alone identifies an optimal power generation mix for 2030 that risks insufficient supply levels, while the iterative feedback loops with the Antares model can ensure the economic effectiveness and security of supply requested by French authorities.

Sector coupling can be a source of flexibility for modern energy systems and has also been assessed via linking approaches. Pavičević et al. [23] investigated its potential by soft-linking the long-term planning multisectoral model for Europe JRC-EU-TIMES and Dispa-SET, a unit commitment and optimal multisectoral dispatch model. Results show different contributions from each individual sector, with the transport sector providing the highest flexibility in terms of power curtailment, load shedding, congestion and CO_2 emissions reduction, while system adequacy and operational costs minimization are better provided by a combination of sources. Model linkage is also at the core of a recent study by Miri et al. [30], where COPPER, a deterministic CEM, is bidirectionally linked to SILVER, a model for optimal economic dispatch, day-ahead unit commitment and optimal power flow with network constraints. From the analysis of the Canadian power system, it emerges that additional transmission and storage capacities are required with respect to what was initially found by the expansion model, that also overestimates wind capacity. Total system costs can be partially offset by improvements in wind curtailment, congestion and load shedding. Linking, therefore, yields important insights that go beyond the findings that can be obtained from a single model analysis, especially in the case of systems with a high penetration of VRE sources.

Soft linking has been adopted in several planning studies for LMICs, often in the context of electrification of rural areas [31,32], while only a few specifically deal with the issue of flexibility representation in power system planning. It is the case of the work by McPherson et al. [33], where IRENA's long-term energy planning model SPLAT (Systems Planning Test) and an electricity system dispatch model developed by the authors are applied to evaluate the integration of VRE sources and electric vehicles for various degrees of decentralization in Zambia. Gaur et al. [34] consider the role of short-term operational constraints on long-term energy system planning through a case study for Northern India. TIMES is used in combination with an extension for unit-commitment to better evaluate the flexibility requirements of high shares of VRE sources.

1.2.3. Modelling studies in Kenya

A range of studies have been undertaken on power system planning for Kenya, which we have been considered to determine our own approach for this study. Carvallo et al. [35] analysed 14 scenarios with a 2035 time-horizon through a 47 nodes model based on the SWITCH long-term planning tool. Results suggest a preeminent role for wind and geothermal, with little to no solar. Selected scenarios evidence a higher sensitivity of geothermal to operational degradation rather than high capital costs, limited sensitivity of the results to CO_2 pricing and the role of diesel and natural gas capacity as flexibility providers. Moksnes et al. [31] introduced soft-linking between OSeMOSYS and OnSSET to account for both the spatial and temporal dimensions of the system. The geospatial analysis shows a key role for solar in bringing universal access to electricity in rural areas, despite the almost negligible contribution to the total annual electricity generation. Finally, Dalla Longa and van der Zwaan [36] evaluated Kenya's nationally determined contributions (NDCs) also in light of the Vision 2030 programme [37]. The analysis, based on the global TIAM-ECN model, finds the target achievable provided that stringent climate change policies are introduced for the residential and transport sectors, while no stringent greenhouse gases abatement targets are needed for the power sector.

Similar conclusions are obtained by Musonye et al. [38] through a TIMES model for the Kenyan power sector. Scenarios are obtained from the combination of two carbon emissions abatement targets and three different levels of demand projections. Results show a penetration of renewable energy sources higher than 50% in all scenarios, except for the one where the business-*as*-usual case is associated to the highest demand level, where the system fails to cover the demand while meeting the reduction targets. Imposing a carbon emission cap implies the addition of higher cost renewables and substantial overcapacity leading to higher electricity unit cost.

Kenya's power system is highly dependent on hydro and geothermal energy resources, which is why Spittler et al. [39] developed a bottom-up system-dynamics model to account for the dynamics of resource utilization. The paper analyses eight different scenarios, based on different demand projections and resource dynamics considerations. Results indicate that higher installed capacities will be required for hydro and geothermal to compensate for production losses.

A LEAP model for Kenya developed by Kehbila et al. [40] includes an extension to internalize the benefits from avoided premature deaths and crop losses from pollution. Seven scenarios are modelled up to 2040 based on government's development plans, regional strategies, and international commitments, all built through a backcasting approach. The fully renewable and SDGs-compliant scenarios show higher overall costs than the scenario backed by the government's plan, yet with lower marginal abatement costs. A recent article [41] presents another LEAP model for Kenya, in this case paired with the optimisation tool NEMO (Next Energy Modeling system for Optimisation). Two scenarios are considered, using a time horizon to 2037. The renewable energy scenario, largely due to the supporting role of storage, is found to be the least cost one.

A synthesis of the main characteristics of each study is reported in Table 1.

1.3. Aim and elements of novelty

As stated earlier, the objective of this study is to inform how Kenya can plan for increasing electricity demand whilst retaining a predominantly renewable system. To do this, we propose the use of OSeMOSYS, a widely recognised CEM, to explore capacity expansion options, soft linked to FlexTool, a PCM, to assess the operability of the future system. The addition of FlexTool is key, given the high renewable shares and the limitations of OSeMOSYS to adequately represent the temporal resolution needed to model operational constraints.

The novelty of our approach is in two regards; firstly, we provide a new logical framework for linking a CEM and PCM, to ensure operability

Table 1
Capacity expansion planning studies for Kenya.

Study	Ref.	Year	Models	Scenarios	Time horizon	Link	Modelling approach
Carvallo	[35]	2017	SWITCH	14	2035	No	CEM
Moksnes	[31]	2017	OSeMOSYS, OnSSET	2	2030	Yes	Soft-link (CEM + GIS)
Dalla Longa	[36]	2017	TIAM-ECN	4	2050	No	CEM
Musonye	[38]	2021	TIMES	6	2045	No	CEM
Spittler	[39]	2021	Self-dev.	8	2050	No	CEM integrated with a system-dynamics model
Kehbila	[40]	2021	LEAP	7	2040	No	CEM
Wambui	[41]	2022	LEAP, NEMO	2	2037	Yes	Hard-link (CEM + interface)
Current	–	–	OSeMOSYS, FlexTool	3	2050	Yes	Soft-link (CEM + PCM)

of future capacity mixes; second, we apply this linking procedure for the first time in the Kenyan context for a CEM-PCM. An approach that provides the benefits of both CEM and PCM characteristics, either linked or in an integrated framework, has never been applied in the Kenyan context. The linking approach is important from a planning perspective in Kenya as it allows for OSeMOSYS to also be applied for wider whole systems analysis – but based on a consistent power system representation.

The remainder of the text is divided in Section 2, where the adopted approach to modelling the power sector is described, Section 3, that presents the data used and how the analysed scenarios have been formulated, Section 4, where all results are presented, and Sections 5 and 6, where results are first discussed and the conclusions drawn.

2. Approach to modelling

In this study, the Kenyan power system is modelled through the linking of a capacity expansion model (CEM), OSeMOSYS [16] and a production cost model (PCM), FlexTool [25]. A more detailed description of how flexibility is represented in the models and the linking procedure is reported in the next subsection, while a general description of the models is given hereafter.

2.1. Description of energy models

The Open-Source energy MOdelling SYStem (OSeMOSYS) is an open-source, bottom-up modelling framework for the long-range optimisation of the energy system and energy mix of user-defined regions [16], where the expression 'modelling framework' indicates software used to generate specific models by populating them with user-defined data, as described in Gardumi et al. [42]. OSeMOSYS is a linear optimisation program that identifies the energy mix that minimises total system costs while meeting the exogenously defined energy demands, subject to predefined constraints. The constraints include conversion efficiencies, relations between different types of energy inputs and outputs, upper and lower limits on investments, energy and power capacity balances, upper limits on emissions and lower limits on renewable energy generation. OSeMOSYS leverages a community of practice built around three pillars, namely, a code management structure, a community forum and outreach activities [43,44]. The full documentation for the model is available online [45].

FlexTool is a power system optimisation model developed by IRENA [24,25], that solves the unit commitment and economic dispatch problem using linear programming. It provides the least-cost optimisation of the generation mix with a detailed power system flexibility assessment. The model can also optimise the best investment options to address flexibility issues. It assumes perfect foresight usually using a time resolution of 1 h or less. FlexTool is an open model and freely accessible [46].

A set of exogenous model parameters is used to describe the Kenyan power system from a techno-economic perspective in both models, ensuring consistency. Specified parameters include available resources (e.g., availability and cost of imported and locally produced fossil resources, availability and intensity of solar radiation and wind); energy conversion technologies (e.g., capacities, efficiencies, and investment and operation costs); transmission and distribution technologies; electricity demand projections; constraints deriving by technical limitations or policy decisions (e.g., political decision to invest in gas power plants rather than coal ones). The implementation of each set of parameters is model-specific and depends on aspects such as the temporal detail considered.

2.2. Approach to modelling flexibility

Unlike many other LMICs, Kenya has a diversified energy mix that already includes a significant share of renewable energy [47], with the potential to increase in the next years. Overcoming capacity expansion models' intrinsic limitations in the representation of energy system flexibility requires balancing the level of detail and computational burden. The approach here is to use a relatively high number of timeslices with chronology information, while soft linking the CEM with a PCM to check for unseen flexibility issues for specific marker years. The linkage also allows consideration of investments in the power sector, combining the long-term perspective of the CEM with the short-term perspective of the PCM.

CEMs use a simplified representation of time based on timeslices. The choice of the number of timeslices depends on several factors, including demand curve shapes, power technologies considered, capacity factor profiles and storage representation [48]. The OSeMOSYS Kenya power sector model used in this study considers 48 timeslices, obtained by the combination of six within-day (i.e. diurnal) timeslices, to account for demand and power production (i.e., solar) variations; four seasons, to consider annual oscillations for wind and hydro capacity factors; and two day-types, to account for varying consumption between weekdays and weekends. A complete description of how timeslices have been defined can be found in the Supplementary material. Multiple daily timeslices in combination with information on their chronological order also enable modelling of the benefits of introducing battery energy storage systems on the grid. Batteries are considered to work with charge-discharge cycles of a few hours and the energy balance is imposed on a daily basis, while pumped hydro's constraint is less stringent and can be balanced up to an annual timescale.

FlexTool represents flexibility through a set of mathematical constraints that account for energy balance, reserve requirements, inertia, ramp-up and down constraints and minimum load. The Kenyan model used in this work has a single node, so it does not consider constraints on power transfer between nodes. The input data has an hourly time resolution. However, to make the model tractable, only a subset of all possible timeslices are selected, covering about 30% of the year. The demand profile for future marker years remains similar to the base year. The import profile is based on OSeMOSYS results: the import amount of each OSeMOSYS timeslice is divided evenly over corresponding hours in FlexTool.

2.3. Approach to model linking

To complement the partial representation of flexibility in OSeMOSYS with the more detailed description in FlexTool, the bidirectional soft-linking procedure outlined in Fig. 1 is applied. First, OSeMOSYS is run for the entire time horizon until 2050. Next, potential flexibility issues are assessed for two marker years: 2030 and 2050, using FlexTool in dispatch mode. Dispatch mode in FlexTool is a run setting where the capacities are fixed, and which assess flexibility issues including lack of reserves, inertia and loss of load. If issues are identified, further FlexTool runs are performed to understand how these flexibility issues could be addressed. Investment mode in FlexTool is first run to provide insights into the type of additional investment that could be made to resolve the issues, followed by a run using dispatch mode to check whether the additional investment deals with any issues. If issues remain unresolved, additional options are evaluated in FlexTool to address the flexibility gaps. Some flexibility issues may remain if the investment required to address them exceeds the penalty cost associated with such issues. Once issues are resolved, a second run is performed in OSeMOSYS, with technology capacities fixed for the marker year that was analysed, but with the additional investments suggested by FlexTool added in. The procedure is then repeated for all marker years considered.

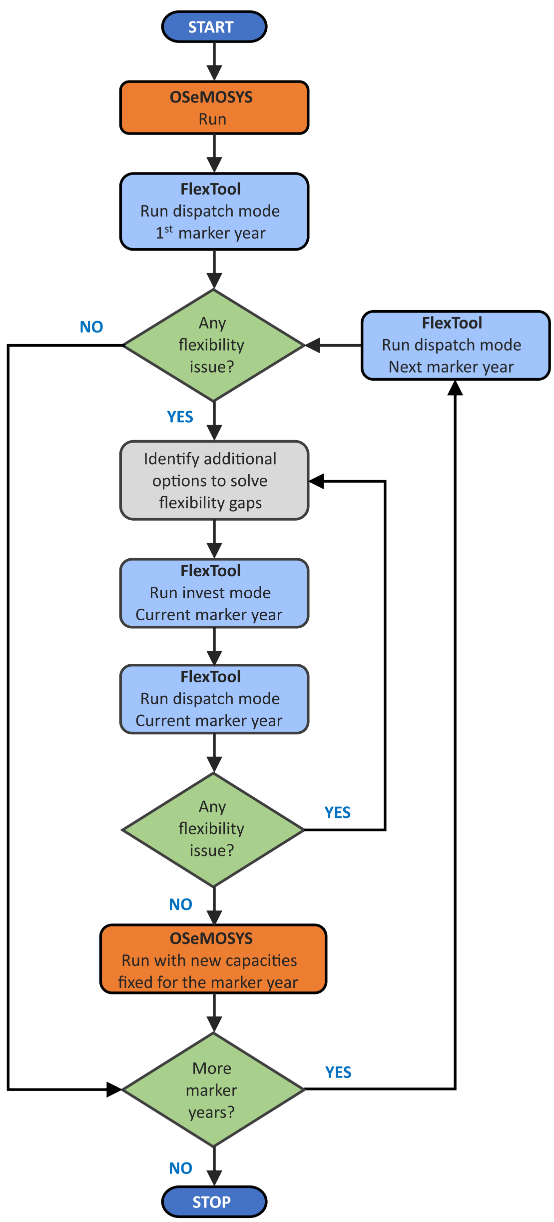

Fig. 1. Soft-linking procedure.

3. Scenario formulation

The scenario analysis using the modelling approach described in section 2 is built around Kenya's Least Cost Power Development Plan (LCPDP). The incorporation of this plan into the modelling is first described, followed by a description of the three core scenarios undertaken.

3.1. Kenya's least cost power development plan

The initial reference energy system for the Kenyan power system was built starting from the available Starter Data Kit [49–51], but has then been comprehensively checked and revised based on more disaggregated data, down to the single power plant level, in line with data from the Medium Term Plan and the LCPDP. The MTP is updated every year by the LCPDP team and is mostly used as an internal document. The latest publicly available version is the 2015–2020 one [4]. At the time of writing, the latest version officially released of the LCPDP was that for 2022–2041 [6], constituting the third update of the long-term plan first published in its 2015–2035 version. The aim of the LCPDP is to inform the committee responsible for the development of the Integrated National Energy Plan (INEP). The document reflects the key requirements outlined by the Energy Act 2019 [52], including the development of an energy plan "in respect of coal, renewable energy and electricity so as to ensure delivery of reliable energy services at least cost". In the current Section, the plan is analysed in terms of demand projections, key considerations on the future capacity mix, and economic assumptions.

3.1.1. Demand

The LCPDP outlines three different demand scenarios, of which two are considered in this study. The reference scenario forecasts a demand increase based on historical growth rates, considering an average year-on-year increase of 5.28%. The high demand scenario is based on the Vision 2030 development framework and considers an average growth in demand of 8.20% per year. Key driving factors include population growth and urbanization rates, GDP growth and the realisation of Vision 2030 flagship projects. A detailed description of demand growth projections by sector can be found in the LCPDP report [6]. Fig. 2 shows the demand projections in terms of annual energy consumption (left-hand side axis) and peak demand (right-hand side axis). Peak demand changes, depending on the temporal resolution considered. The peak demand in FlexTool, working at hourly resolution, is much higher than OSeMOSYS, where the demand is redistributed through the timeslices. The LCPDP projections are limited to 2040 and are complemented up to 2050 with data from The Electricity Model Base for Africa (TEMBA) included in the Kenya Data Starter Kits developed by Allington et al. [49, 50].

Annual electricity demand is divided between three end-use sectors (commercial, residential and industry) using IEA energy balance data for the base year of 2019 [53]. The representation of demand is relatively static, in that the relative share of electricity demand between the three sectors does not change through time. The annual demand profile for each sector is provided on an hourly timestep and does not change from one year to the other.

3.1.2. Power plants

The LCPDP includes two capacity expansion scenarios, one based on a list of candidate plans and the other on an optimisation procedure. A set of recommendations are included and have been considered to compile the list of power plants for this study. Peaking capacity power plants and battery storage are suggested as solutions in the short term to reduce the amount of vented steam during off-peak hours, provide

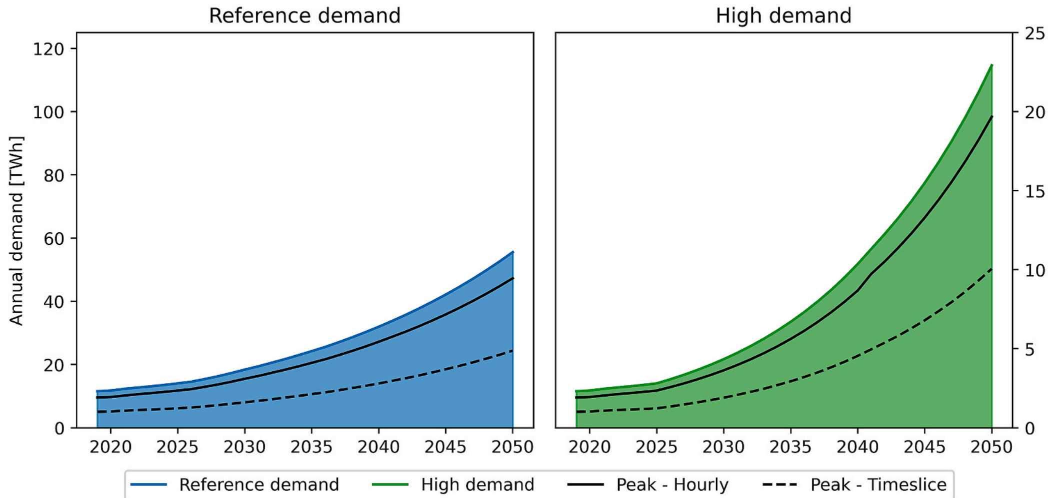

Fig. 2. Demand projections for the LCPDP reference and high demand cases. Black solid lines represent peak demand when considering hourly timesteps, while black dashed lines represent peak demand for aggregated timeslices.

system reserve and prevent load-shedding in Western Kenya. In the longer term, for the same purpose, LNG gas turbines, pumped hydro storage and hydro dams are to be considered as potential solutions. Transmission capacity from Ethiopia is also considered, up to 200 MW in the short term, and up to 400 MW after 2026.

Power plants are characterized by capacity bounds, efficiencies, capacity, availability factors, investment and running costs. Each plant is considered either to be already existing, planned or a candidate power plant. Power plants already existing in 2019 constitute the residual capacity and are considered to be online until their retirement year. Planned power plants are those included in the MTP and have a given capacity and a Commercial Operation Date (COD) set. The MTP has a five-year time-horizon, hence there are no planned power plants after 2027. Candidate plants are only defined by the available capacity and an earliest COD. The resulting available capacities obtained from the LCPDP are shown in Fig. 3.

For geothermal, hydro, solar and wind, additional generic technology options were added after 2025 to account for the gap between the technical potential and the planned capacity of each renewable resource. Each additional capacity is characterized through a seed value and a growth rate. Table 2 provides detail for the technical potential for each renewable resource, while Fig. 4 shows a comparison between aggregated upper capacity bounds obtained from the LCPDP and the estimated potential capacity for geothermal, hydro, photovoltaics, and wind resources.

3.1.3. *Economic assumptions*

Cost data are obtained from the power plant database used to compile the MTP and LCPDP, and input on a plant-by-plant basis. Table 3 and Table 4 show ranges of capital and fixed operating cost ranges across power plants grouped by primary energy sources. For generic technologies a capital cost increase of 10% with respect to the most expensive power plant of the same technology is assumed: this ensures that generic technology options are selected only after all candidate plants have been built by the model. O&M costs associated to hydro, solar, wind and batteries are just considered on an annual fixed basis, and variable costs are hence null.

Future costs of power generation technologies are highly uncertain, with variable renewables (solar and wind) in particular exhibiting huge

Table 2
Generic technologies remaining potential, upper bound.

Renewable resource	Remaining potential [GW]	Seed value	Growth rate	Ref.
Geothermal	6.7	0.125	8.7%	[54]
Small hydro	0.1	0.016	9.4%	[55]
Large hydro	0.8	0.098	9.3%	[55]
Solar	14.8	0.051	31.6%	[56]
Wind	15.1	0.057	22.7%	Own assumption[a]

[a] Capacity addition grows from a seed value of 0.06 GW/year in 2026 to 1 GW/year in 2040, and is then held constant.

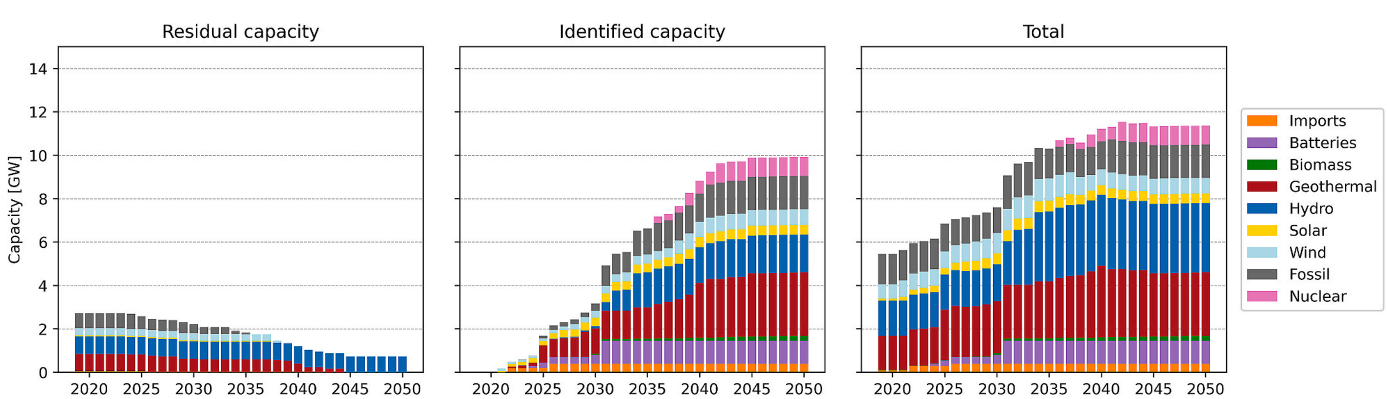

Fig. 3. Residual power capacity (left) compared to identified capacity (centre), composed by planned and candidate plants. The sum of residual and identified capacity is the total capacity (right) part of the Long Term Plan.

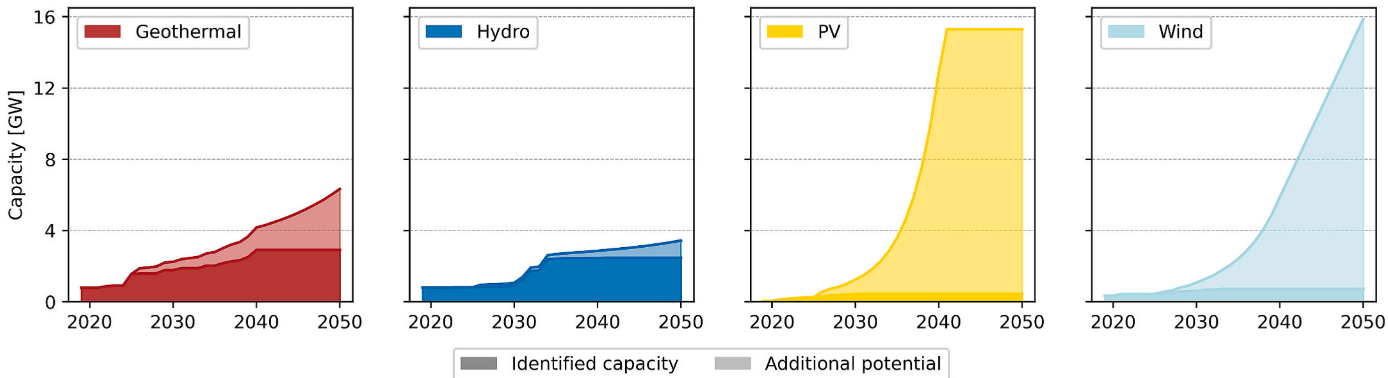

Fig. 4. Available capacity from renewable energy sources. Dark colours indicate available capacity already accounted by the LCPDP, lighter colours the additional capacity introduced in the model based on the estimated potentials listed in Table 2. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 3
Cost assumptions for low-carbon power sources. Intervals include both variations in time and between different power plants. All costs from LCPDP [6], except for nuclear [57] and batteries [58].

Technology	Capital cost [M$/GW]	Fixed O&M cost [M$/GW/year]	Variable O&M cost [M$/PJ]
Biomass	2500	75	0.2
Geothermal	1100–4900	20–450	0.14
Hydro	2700–4500	15–125	0
Pumped hydro	1150	15	0
Solar	650–1500	15–26	0
Nuclear	5000	8	0.13
Wind	1600–1900	71–76	0
Batteries	732–1483	18–37	0

Table 4
Cost assumptions fossil fuels power plants. All costs from LCPDP [6].

Technology	Capital cost [M$/GW]	Fixed O&M cost [M$/GW/year]	Variable O&M cost [M$/PJ]
Coal	2500	66	0.36
Heavy-fuel oil	1400–1700	32	2.4
Natural gas	850–1350	21–33	3.7
Light-fuel oil	1250	21	3.5

cost reduction potential [59]. In the reference scenario a modest learning of 0.3% capital cost reduction per year is applied, leading to an average capital cost of 735 $/kW for solar and 1650 $/kW for wind in 2050. A single social discount rate of 8.9% has been applied to all costs in the model, in line with the average interest rate of the Central Bank of Kenya of the last 10 years [60].

3.1.4. Flexibility assumptions

The technical and economic assumptions for each technology, the fuel costs are aligned between OSeMOSYS and FlexTool. However, due to the temporal disaggregation of the FlexTool model, the capacity factors for wind and solar, and the inflows for hydro power plants are provided at an hourly level, whilst aggregated to the timeslice level in OSeMOSYS. Moreover, the storage usage of the hydro power plant with dams is optimized by the model. The imports are not optimized in FlexTool, they are fixed based on the OSeMOSYS results. The amount of energy for a given OSeMOSYS timeslice is equally distributed between the corresponding hours. Total electricity demand is aligned between the two models. The hourly demand profile is based on the 2019 profile and stays similar for the following marker years.

The penalty costs associated with the different constraints explained above are shown in Table 5 and have been agreed with the LCPDP team. For each year, the inertia limit I_{lim} is computed using the following formula:

$$I_{lim} = \frac{f}{2} \cdot \frac{P_{loss}}{RoCoF} \tag{1}$$

with f the nominal frequency of the system which is 50Hz for the Kenyan power system, P_{loss} the maximum power that could be lost and $RoCoF$ the rate of change of frequency. The rate of change of frequency has not been fixed for the Kenyan power system, but for this study, a value of 1 Hz/s was taken. The amount of inertia thus depends on the year considered as the maximum power loss changes according to the marker year. The reserves margin is computed based on a similar method than in OSeMOSYS: firm capacity equivalent to a share of 10% of the demand is required at each hour.

Finally, the computation time to run FlexTool for the whole year would be too resource intensive. Thus, 33% of the hours are selected covering the weeks with the highest and lowest net load and the highest and lowest inflow. In addition, one week out of every four is also included to capture each month of the year.

3.2. Modelled scenarios

The first two scenarios are based on the two different demand projections previously illustrated from the LCPDP plan. The reference scenario considers the capacity bounds as per the LCPDP and the estimated renewable resources potential, as outlined in sub section 3.1.2. The high demand scenario requires increased capacities to meet demand requirements. Four gigawatts of extra capacity are introduced both for batteries and natural gas power plants, as to guarantee freedom to the model to choose whether to develop intermittent renewable energy sources plus storage or fossil fuel peaking plants.

To account for the high variability in projected capital costs for renewable energy sources, a third scenario is added. In the low-cost renewables scenario, solar and wind power plants are projected to decrease their costs from the 2019 levels to the average global costs of the IEA's World Energy Outlook 2022 Net Zero scenario [57]. Photovoltaic panels' capital cost decreases from an average of 1288 $/kW in 2019 to 308 $/kW in 2050, while wind goes from 1781 $/kW to 1090 $/kW.

The specific modelling assumptions for each scenario are summarised in the following.

Table 5
Penalty assumptions in FlexTool.

Loss of load [$/MWh]	Loss of reserves [$/MWh]	Lack of inertia [$/MWs]	Lack of capacity [$/MWh]
1500	1000	30000	5000

- Reference (REF). Electricity demand is aligned with the LCPDP reference projections. Residual capacity, committed and candidate power plants follow the plans as in the MTP and LCPDP. Additional renewable sources potential starts to be available after 2025 with exponential increase in available capacity. Nuclear is available from 2036.
- High demand (HD). All reference scenario assumptions stand, but higher demand is assumed according to the Vision 2030-compliant LCPDP's demand projections. The potential of renewable energy technologies is increased of 10%, as higher demand justifies the exploitation of less economic resources. An extra 4 GW capacity is made available to the models after 2030 both for battery storage and natural gas to cover additional flexibility requirements while letting the models free to choose between options.
- Low-cost renewables (LCR). As per reference scenario but with projected higher costs reduction for renewables.

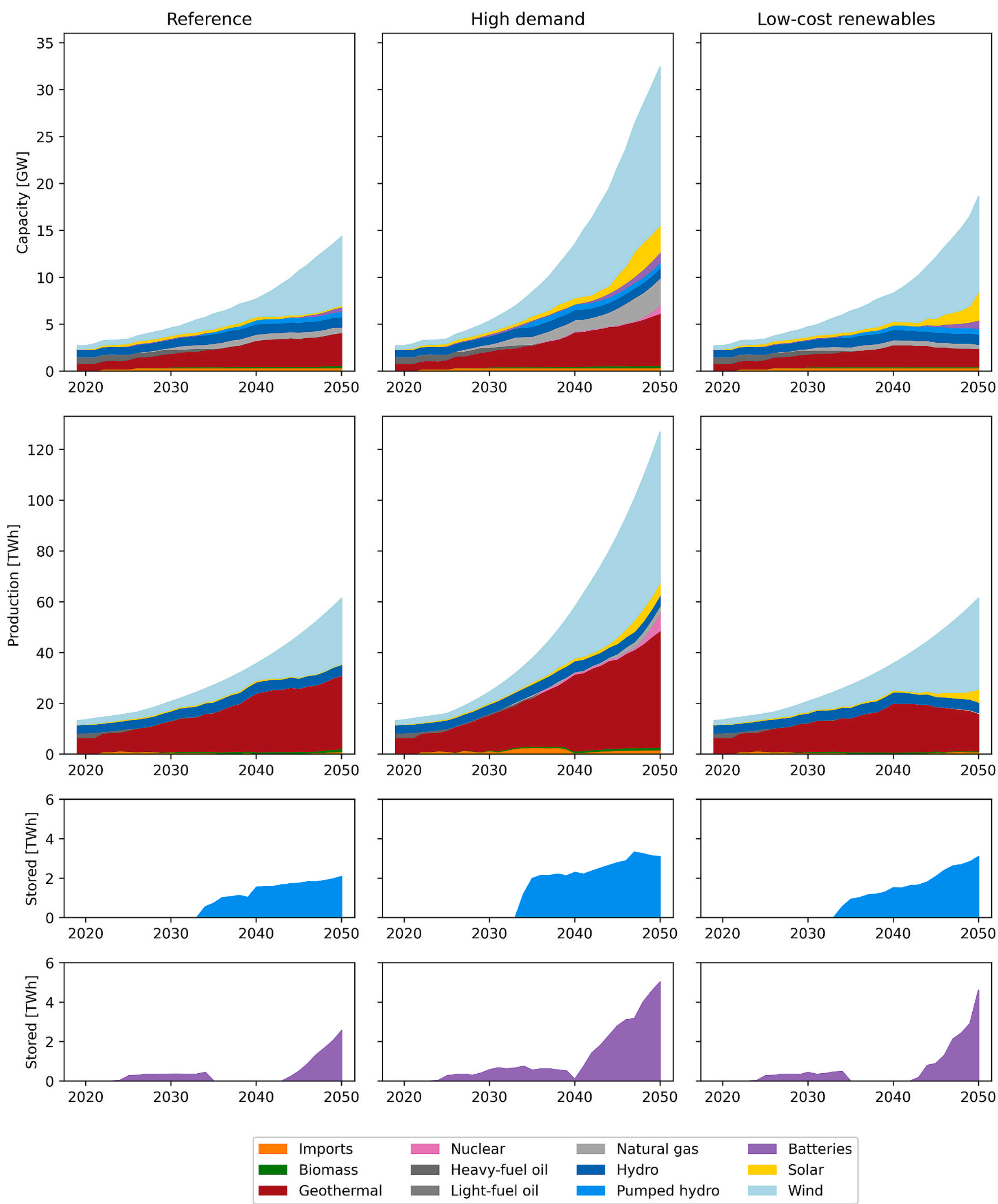

Fig. 5. Capacity and electricity production by generation type across the modelled scenarios. Production from storage technologies is shown separately to avoid double counting.

4. Results

This section outlines the results obtained for the Kenyan power sector in the three scenarios considered, reference (REF), high demand (HD) and low-cost renewables (LCR). Results are presented through comparison with first OSeMOSYS runs, and the subsequent linking with FlexTool to generate further OSeMOSYS simulations.

4.1. OSeMOSYS power system pathways prior to flexibility assessment

As shown in Fig. 5, the initial capacity installed in 2019 is 2.7 GW, which grows to 14.4 GW in the REF scenario in 2050. The most significant capacity increase is for wind, which grows from around 300 MW to more than 7.3 GW, and geothermal, increasing from 800 MW to 3.5 GW. In generation terms, geothermal dominates due to higher capacity factors, maintaining a higher share throughout the time horizon, from 6.6 TWh to almost 30 TWh, corresponding to 44% of the total electricity demand, with wind reaching 42% in 2050 (compared to a capacity share of 51%). Installed hydro capacity remains almost constant from 2019 to 2050, reaching slightly more than 1 GW.

Fossil fuel power plants and solar tend to have a marginal role in the energy mix. Oil power plants tend to be substituted by natural gas ones at the end of their operational life. The installed capacity is only required by the model to meet the reserve margin requirements, as no production from fossil fuel power plants is realized. Overall storage capacity gets to 1.1 GW in 2050, almost equally split between pumped hydro (0.6 GW) and batteries (0.5 GW). Pumped hydro is built earlier on, while batteries only come into the mix from 2044. Both storage technologies enable the production from non-dispatchable power sources to be shifted in time to meet demand.

The HD scenario shows a more than two-fold increase (125%) in capacity installed in 2019, reaching 32.4 GW in 2050. In generation terms, the increase is 106%, lower than the capacity increase due to a higher reliance on renewable technology with lower capacity factors. The role of wind is similar to the reference scenario, with all available capacity of 16.8 GW built by 2050. In this scenario, wind is not only the major resource on a power basis, but also on an energy one, producing 59 TWh out of 135 TWh, compared to the 46 TWh of electricity from geothermal resources. Geothermal also sees all available capacity installed. The same goes for storage technologies, which enable a higher share of solar capacity to be installed, totalling 2.9 GW in 2050, at 9% of the system share. As the model is tightly constrained towards the end of the time horizon, nuclear is also part of the capacity mix, and all the three 300 MW units available are built. A significant amount of geothermal capacity becomes available around 2040, where a step increase can be observed. The lower capacity available between 2030 and 2040 is compensated by a temporary increase in electricity imports, reaching 2.8 TWh/year around 2035.

Finally, the LCR scenario sees a significant increase in wind and solar installed capacities, reaching 10.1 GW and 3 GW respectively, taking the total installed capacity to 18.6 GW. The increase in VRE sources is partially compensated by a decrease in geothermal capacity, dropping to 2.4 GW, after peaking at 2.8 GW in 2040. The steady increase in geothermal capacity to 2040 and the subsequent decrease (despite demand continuing to grow), suggests that around 2040 solar plus storage reaches cost parity with geothermal, in essence behaving like a dispatchable energy source. As in the other scenarios, no substantial change in the amount of hydro capacity installed is observed. Natural gas capacity is around 0.5 GW with respect to the 0.6 GW of the reference scenario, almost without producing any electricity at all. This capacity is expected to be used minimally as a reserve measure.

4.2. The use of FlexTool for assessment of system flexibility

The OSeMOSYS results were then assessed in FlexTool for 2030 and 2050 marker years. The results reported below are for the FlexTool model only. The REF scenario has a minor reserve shortfall by 2030 as 0.25% of total reserve requirements are not met. However, FlexTool's suggested investments in hydro, geothermal, natural gas and batteries lead to a higher cost than the equivalent cost penalty incurred for the reserve deficit. Thus, the suggested mix of capacities by FlexTool is for no change to those provided by OSeMOSYS (Fig. 6). By 2050, flexibility issues are more significant. Loss of load occurs on 1.7% of total annual demand and reserves are 4.3% too low, leading to a penalty for the system of about 2000 M$. FlexTool's suggested investments (Fig. 6) amount to 1000 M$ and decrease the total cost of the system from 3300 to 2300 M$, by eliminating loss of load and decreasing the insufficient reserves to less than 0.1%. For both marker years, the inertia constraint is satisfied.

For the HD scenario in 2030, reserves are about 0.6% short of the requirement. As in the REF scenario, FlexTool's suggested investments lead to a higher system cost, and therefore the optimal mix capacities do not change compared to the ones provided by OSeMOSYS (Fig. 6). By 2050, insufficient reserves of 7% of the total requirement are observed, while loss of load occurs for more than 1% of total annual demand. The associated penalty amounts to almost 4000 M$. The model chooses to invest in all available gas power plants, in almost all available hydropower plants, in 6 GW of solar PV with 4 GW of batteries. All geothermal capacities have already been built in OSeMOSYS so there is not an option to increase this. These additional capacities eliminate loss of load and reduce insufficient reserves to less than 0.04% of the total required. Despite 1750 $M of investment, the system cost decreases from 7400 M$ to 4700 M$. For both years, the inertia constraint is satisfied.

In the LCR scenario, in 2030 reserves are about 0.5% short of the requirement while the loss of load is almost negligible (less than 0.01% of total demand). However, due to its RES shares, inertia is 0.01% short of the requirement, leading to a higher penalty than in the other scenarios, of 400 M$ compared to less than 20 M$. The suggested investment by FlexTool (Fig. 6) in geothermal, hydro, natural gas and batteries eliminates all flexibility issues. The system cost decreases from 840 M$ to 650 M$. By 2050, loss of load affects more than 3.5% of the demand and reserves are 3% short of the requirement. The suggested investments do not eliminate all flexibility issues but decrease them to less than 0.05% of total demand for loss of load and to 0.7% for the insufficient reserves. They amount to 1000 M$. The system cost decreases from 5100 M$ to 2600 M$.

4.3. Revisiting OSeMOSYS scenarios based on flexibility insights from FlexTool

Fig. 7 shows, for the marker years considered, the differences in electricity production from each generation type across the three modelled scenarios. For each scenario, results are reported for OSeMOSYS' first run (OS pre-FT), FlexTool (FT) and OSeMOSYS' final run, with additional capacities fixed from FlexTool (OS post-FT). Given the linking procedure, the capacities installed in the system for the FT and the OS post-FT runs are always the same, while the OS pre-FT run capacities change according to Fig. 6. In FlexTool, imports are fixed as provided by OSeMOSYS. Therefore, no changes in imports can be seen between the OS pre-FT and FT runs, while changes might appear in the OS post-FT case, as capacities imposed by FlexTool lead to more production from non-dispatchable sources.

Across all scenarios a difference in hydro production can be noticed. This has to do not only with different installed capacities (as between pre-FT and FT runs), but also with differences in how hydro power plants are modelled in OSeMOSYS and FlexTool. OSeMOSYS directly relies on capacity factors estimated per each power plant, while FlexTool uses inflows data and considers the capacity of storing water, and hence energy, of dam hydro plants to optimise the hydropower production.

Lower production from hydro is compensated in OSeMOSYS by higher shares of geothermal and heavy-fuel oil. Solar and wind productions are generally consistent through scenarios with equal installed

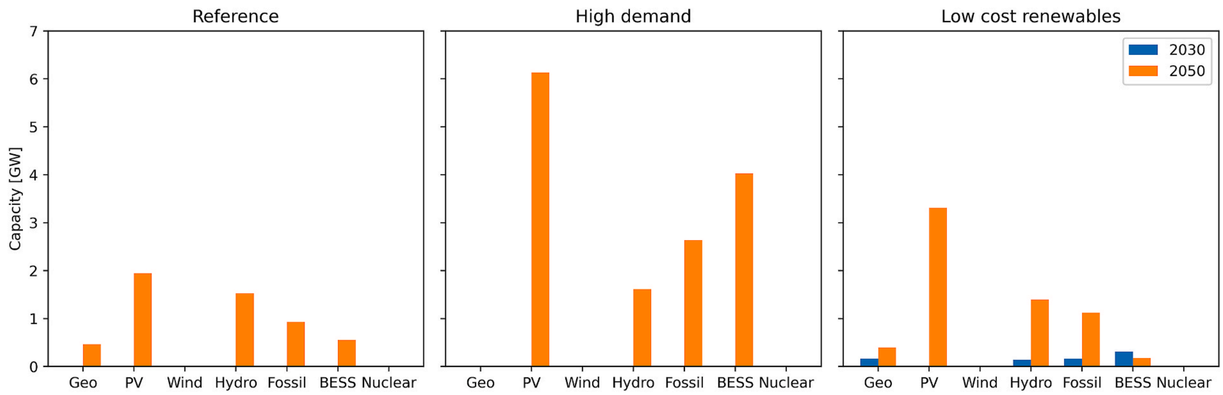

Fig. 6. Additional capacity requirements for considered marker years.

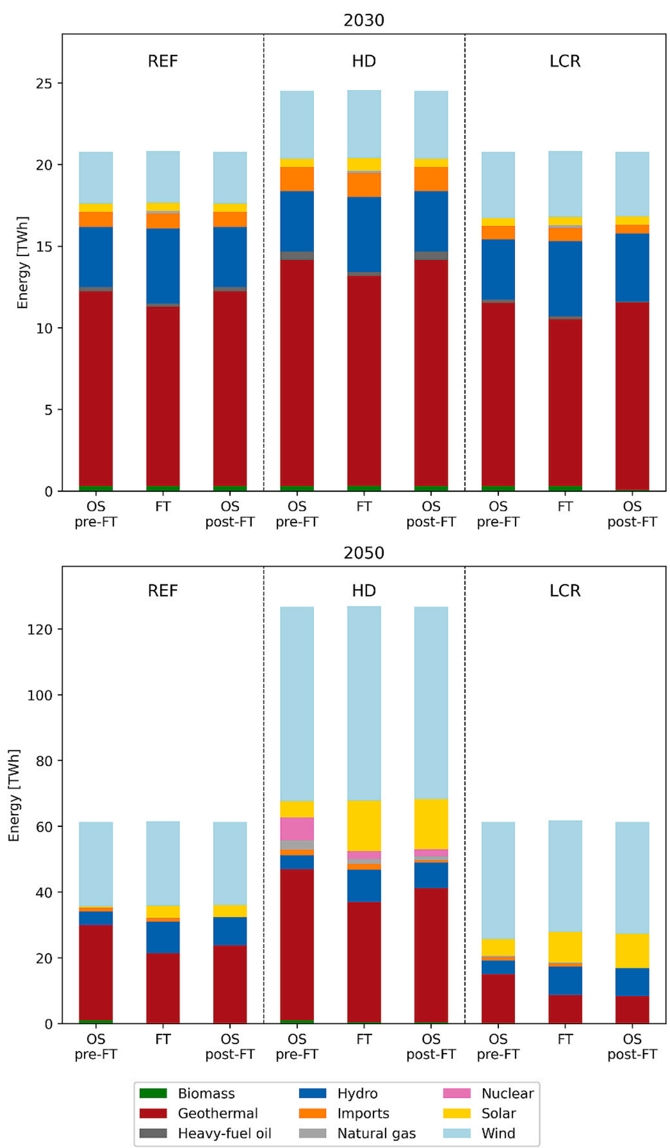

Fig. 7. Electricity production comparison across modelled scenarios at different stages of the linking procedure for the marker years considered. *OS pre-FT* is OSeMOSYS runs prior to flexibility assessment using FlexTool; *FT* is the flexibility assessment using FlexTool; *OS post-FT* is OSeMOSYS runs adjusted based on FlexTool assessment.

capacity. In the 2050 LCR case, the production from solar modelled in OSeMOSYS is higher than the one estimated by FlexTool. In this case, the installed capacity in OSeMOSYS, and hence the production, is higher than the one in FlexTool, due to lower capital costs of solar, resulting in OSeMOSYS installing more panels and cutting imports from Ethiopia, leaving the interconnection line unused. The same does not happen in FlexTool as imports are exogenously imposed. Nuclear appears in the mix only in the HD scenario, and it is used in the FT and OS post-FT runs as a highly dispatchable unit, in net contrast with the usual role of nuclear as baseload.

Minor variations in the production levels between FT and OS post-FT runs are due to two main factors. First, the different time representation in the two models, and second, the different estimates of curtailed renewable electricity due to the different grid constraints imposed in the models.

4.4. Total cost and emissions

Total costs are estimated from the OSeMOSYS modelling. A comparison between pre- and post- FlexTool runs is shown for each scenario in Fig. 8. Given the projected demand increase for Kenya, capital costs represent by far the higher share of total costs, as new capacity has to be built not only to substitute retired plants, but also to meet demand growth. The highest difference, both in absolute and relative terms, is obtained in the LCR scenario, where the high penetration of VRE makes it crucial to have an improved representation of flexibility requirements and subsequent capacity investments required. The total difference of 1.1 billion dollars is entirely due to the difference in capital cost, with minor contributions from the other cost components.

Annual emissions from the power sector in Kenya are projected to be relatively low in all scenarios, thanks to a high penetration of renewable energy sources (Fig. 9). In the scenarios where the REF demand projection is considered, emissions get close to net-zero. FlexTool's and OSeMOSYS' updated runs have the same capacities installed, and differences in emission levels are only due to the way the system is operated, hence FlexTool provides a more accurate picture of what the annual emissions could be given the capacity mix. The higher variation seen in 2050 in the HD scenario from the pre-FT run compared to the other two is due to the higher utilization of natural gas power plants, that is reduced by the much higher PV capacity and batteries installed in the FlexTool run (see Fig. 6).

5. Discussion

The results of the modelling highlight that Kenya is well placed to maintain its very low carbon generation system while meeting growing demand in future years. This is primarily through the use of its significant wind and geothermal resource bases, as shown across all scenarios. The modelling points to geothermal providing firm generation,

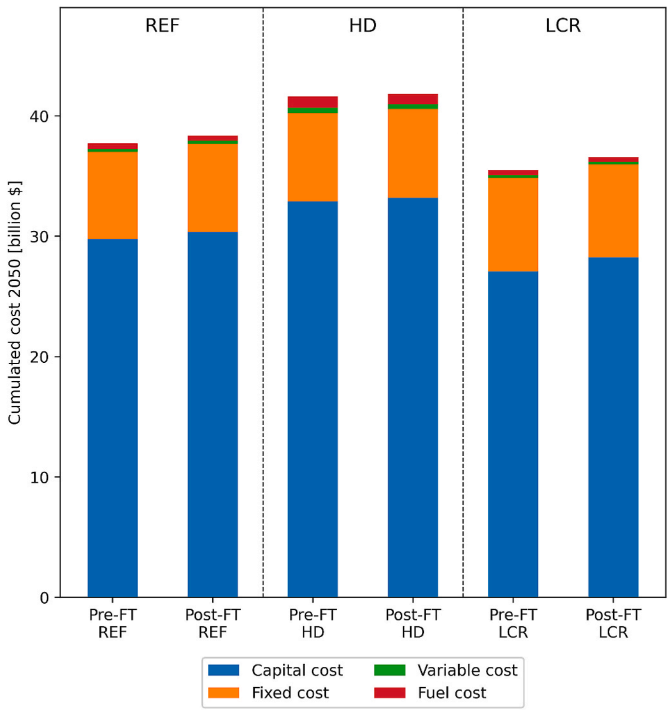

Fig. 8. Pre- and post-linking total cumulated system costs 2050.

alongside an increase in storage, helping manage the variable generation from a large increase in wind capacity. Kenya has particularly strong experience in developing its geothermal resources; however, experience of developing wind projects is less established. To achieve the growth in wind shown in this analysis, Kenya will continue undertaking wind resource assessment for detailed wind mapping which include zonation of promising areas for wind energy development, facilitation of investments in large scale energy projects, and informed decision making for public and private sectors deployment of wind resources. Additionally, Kenya will develop the Renewable Energy Auction Policy aimed at attracting private sector investments in electricity generation from renewable energy sources as a means of diversifying national power sources and enhancing national energy security.

Solar also has a key role to play, particularly in HD and LCR cases, but key to this in a system with high renewable shares will be battery storage. Both solar and wind deployment ramp up in the mid-2030s, as they become increasingly cost-competitive, alongside storage options that are required for system flexibility. To the mid-2030s, it is geothermal that plays a key role in meeting demand growth. It is notable that there is no role for nuclear, except in higher demand scenario, when the availability of other options is constrained. Whilst this technology does come into play, it should be noted that it does not operate as per standard operation of such plant, which tend to be run at high load factors to recuperate costs. In fact, the low load factors observed in the CEM highlight that nuclear is ill-suited to a high VRE system as in reality such plant would need to run at much higher load factors to be economic.

As the Kenyan government plan to maintain a high renewables system, it will be key that they ensure the system flexibility, to maintain a reliable supply as demand grows. This analysis has highlighted that for such systems planning tools that do not consider flexibility requirements in sufficient detail may result in poor investment choices. Hence the proposed approach that links analysis of capacity expansion using a CEM, with a PCM that provides insights on system operation and flexibility. Whilst the CEM in this study provides a reasonable estimation of a system that can meet the needs of high demand in a renewable dominated system, a number of issues highlight the importance of the PCM analysis.

Solar contribution is underestimated by the CEM, with several additional GWs installed by 2050 for all scenarios after implementing the linking procedure. The more detailed time representation of the PCM identifies additional grid flexibility requirements, most of which can be met by renewable capacity, with only a minor role for dispatchable fossil fuel-based generation. This is a crucial insight that highlights the potential development of the system whilst remaining very low carbon. From the CEM analysis only, fossil fuel plants are built to meet reserve margin requirements, but not used at all. The PCM highlights some limited use of these plants but confirms the capacity requirement mainly to meet the reserve margin. Future developments could include a more in depth look at the level of reserve margin required to ensure proper security of supply. To provide the inertia required by the system, geothermal plants are used, playing a crucial role in minimising the use of fossil fuel plants. The PCM also identifies a stronger role for hydro power plants although this has not only to do with time discretization, but also with differences in how they are modelled.

Crucially, the soft linking approach identifies critical issues in all scenarios, but mostly in 2050, when VRE penetration is higher. The importance of this linking approach in a system with high VRE penetration is confirmed by the results for the LCR scenario, where key additional capacity is already identified in 2030. Additional total system costs tend to be low in relative terms, but reach 1.1 billion $ in absolute terms, confirming the importance of linking to have better cost estimates.

Kenya's power sector has a highly diversified set of energy sources, with a high penetration of renewables and low emissions. This trend

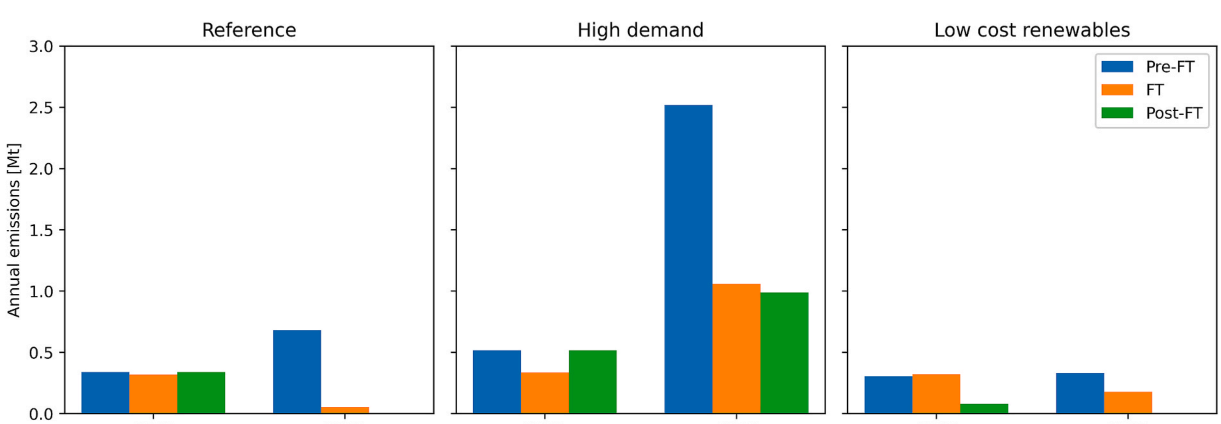

Fig. 9. Annual emissions comparison across modelled scenarios at different stages of the linking procedure for the considered marker years.

could be maintained in the future even for high demand projections, getting close to net-zero emissions even for cost-optimal scenarios where a climate constraint is not included. Results emphasise the increasing competitiveness of renewables and suggest that Kenya could avoid the risks associated with lock in effect of fossil fuels investments.

6. Conclusion

A novel soft linking strategy for CEMs and PCMs has been outlined and tested to analyse the optimal generation mix of the power system and has proven to be effective in identifying key potential flexibility issues and necessary investments to address them. The procedure is based on well documented open-source models, used and maintained by an international community of users, making it accessible and transparent for energy planners and stakeholders in Kenya as well as other sub-Saharan countries or LMICs more in general. Kenya could reinforce its role as regional leader in the adoption of renewable energy sources and energy system planning practices. The modelling results show that Kenya is well placed to maintain its high levels of renewable electricity reaching almost 100% in all scenarios while meeting the projected demand increase, leveraging especially on its geothermal and wind resources. The total installed capacities range from 1.9 GW to 3.5 GW for geothermal and 7.3 GW–16.8 GW for wind by 2050 depending on the demand growth projection. The main challenges for achieving the high renewables penetration are ensuring adequate flexibility in the system to avoid loss of load and ensuring enough reserves in the system to face unexpected changes in the power system. Inertia levels are satisfied in all scenarios but stricter requirement for instance in the rate of change of frequency (RoCoF), which is used to control the stability of the power system, could lead to additional constraints in the system.

Potential improvements of the current work include the extension of the outlined procedure to include more marker years, starting with 2040, and a regional disaggregation of both models. Additional sources of flexibility could also be considered, such as demand response. Demand flexibility and long-term storage might help reduce reliance on natural gas peaker plants, especially if extending the time-horizon beyond 2050. Reserve margin has proven to be a key parameter driving the installation of fossil fuel resources, suggesting that a more extensive critical assessment of the level of reserve could be beneficial. Future developments could also look at the climate change impact on hydropower generation, the integration of geospatial information on renewable resources, as well as the introduction of methods to account for modelling uncertainty.

CRediT authorship contribution statement

Mungai Kihara: Conceptualization, Resources, Writing – original draft, Supervision, Project administration. **Pietro Lubello:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Ariane Millot:** Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Michelle Akute:** Conceptualization, Data curation, Writing – review & editing. **Julius Kilonzi:** Data curation, Writing – review & editing. **Monicah Kitili:** Data curation. **Felister Mukuri:** Data curation, Writing – review & editing. **Boniface Kinyanjui:** Writing – review & editing. **Pooya Hoseinpoori:** Conceptualization, Methodology, Software. **Adam Hawkes:** Writing – review & editing, Funding acquisition. **Abhishek Shivakumar:** Conceptualization, Methodology, Software. **Dan Welsby:** Conceptualization, Methodology, Software, Validation, Data curation. **Steve Pye:** Conceptualization, Methodology, Software, Validation, Data curation, Writing – original draft, Writing – review & editing, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data and models used in this paper can be accessed at: http://doi.org/10.5281/zenodo.8337794

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Appendix A. Supplementary data

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