

An investigation of the impact of bounded rationality on the decarbonisation of Kenya's power system

Authors

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Summary

A low-carbon energy transition is required to induce sustainable economic growth around the world. The strategies to achieve such a low-carbon transition, however, must be robust in the face of uncertainty. In this work, we propose a robust low-carbon transition of Kenya's power sector, integrating two complimentary methodological approaches, an optimisation (OSeMOSYS) and agent-based (MUSE) approach. The work provides insights about how policies could be tailored to modify investors' preferences and achieve a low-carbon transition at lower societal costs. The insights could be extended to similar economies in the global south, as well as more broadly, around the world.

Extended abstract

The Paris Agreement, signed in 2016, has a long-term temperature goal to keep the rise in global average temperatures to well below 2°C above pre-industrial levels, and to pursue efforts to limit the increase to 1.5°C [1]. For this to be achieved, a global transition to a low-carbon energy system is required.

The population of Africa is set to grow rapidly. It is projected that one-in-two people added to the global population between 2021 and 2040 are set to be African [2]. These profound demographic changes are set to drive economic growth, infrastructure development and, in turn, energy demand [2]. Kenya is no different in this regard, and has the goal of achieving universal electricity service to all households and businesses by 2022 [3]. Such a rapid transformation requires in-depth planning to assess robust strategies in the face of uncertainty.

The power system is central towards this decarbonisation goal; the power system can reduce emissions from multiple energy sectors, including transport and cooking. Figure 1 shows the emission projections until 2030 for Kenya. The emissions from the energy and power sector increase significantly in the Second National Communication (SNC) to the UNFCCC scenario [4]. To be consistent with the Paris Agreement, it is important to reduce these emissions to zero. The insights derived from this case-study on Kenya's power sector has broad implications for other similar economies around the world.

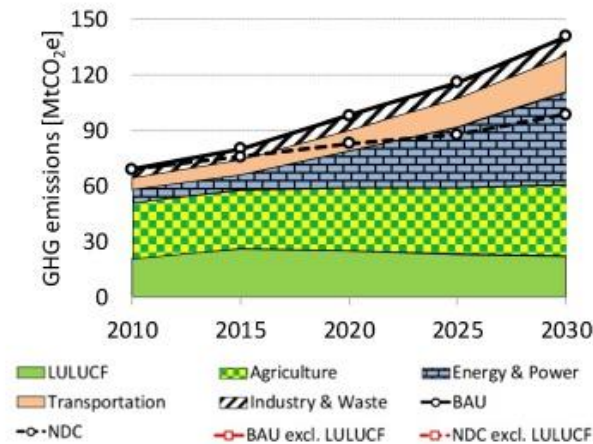


Figure 1: Greenhouse gas emissions in Kenya, according to its Second National Communication (SNC) to the UNFCCC [5]. Where BAU is business as usual, LULUCF is land use, land use change and forestry and NDC is a Nationally Determined Contribution.

The objective of this research is two-fold: to model the decarbonisation of the power sector in Kenya, and to investigate the impact that bounded rationality has on decarbonisation scenarios. This study will compare decarbonisation scenarios using two different integrated assessment model (IAM) approaches: agent-based and optimisation-based. This work will compare OSeMOSYS, a systems optimisation model for long-run energy planning with the ModULAR energy system Simulation Environment (MUSE) [6], [7], a novel open-source agent-based integrated assessment model, which can capture market imperfections due to the bounded rationality of agents [8].

Models based on optimisation such as OSeMOSYS, use build long-term scenarios based on a total system cost minimisation. Despite providing invaluable insights on how certain targets can be achieved in an optimal way, their analysis suffer from several limitations. Primarily, they assume that a central actor co-ordinates investment decisions within an energy system, that this central actor has perfect knowledge of the future and that the ultimate goal of this actor is cost minimisation. These models, however, do not characterise individual investor behaviour, which may deviate from a simple cost-minimisation approach. These drivers can be explained by a sociological, psychological and organisational approach [9].

With a view to model heterogenous investor behaviour, limited foresight, and bounded rationality in energy investments, agent-based models have gained high interest. In this work, we investigate how agent-based models can offer a complimentary methodology to traditional optimisation-based approaches with a focus on Kenya's power sector transition. This provides policy makers with additional information and knowledge that would have been lacking by relying solely on the traditional, optimisation-based methods.

The agent-based model which will be investigated in this work, MUSE, identifies plausible alternative mitigation pathways through explicit bottom-up modelling of technologies. MUSE models detailed operating and capital cost projections per technology, amongst other physical properties such as utilisation factor. MUSE models economies of scale through the reduction in price of technologies, which reduces proportionally with installed capacity. MUSE models agents as independent investors which can prioritise different objectives such as cost minimisation, comfort, or fuel costs. Further, MUSE models investor behaviour

based on limited knowledge of the future. This more closely models the behaviour of real-life investors who must make decisions under uncertainty of the future. This is in contrast to the traditional optimisation-based approach, which assumes knowledge of the future is known at the start of the simulation.

Currently two-thirds of Kenya's energy currently comes from bioenergy [3]. However, the ability of geothermal resources, solar and wind, amongst others to fill this gap and reduce emissions from the power sector will be explored. The limitations and differences between the model results will be surveyed and contrasted and put into a wider context.

Figure 2 displays projections by the IEA for both the Africa Case and Stated Policies Scenario (SPS) case. They show a large uptake in geothermal, hydro, wind and solar PV between 2010 and 2040, which are based upon an optimal pathway. The ABM modelling would provide a different technology portfolio depending on the agents' propensity to risk due to uncertainty in bioenergy availability, access to capital to finance carbon capture and storage projects [7], as well as availability of electricity storage to balance renewables intermittency [6].

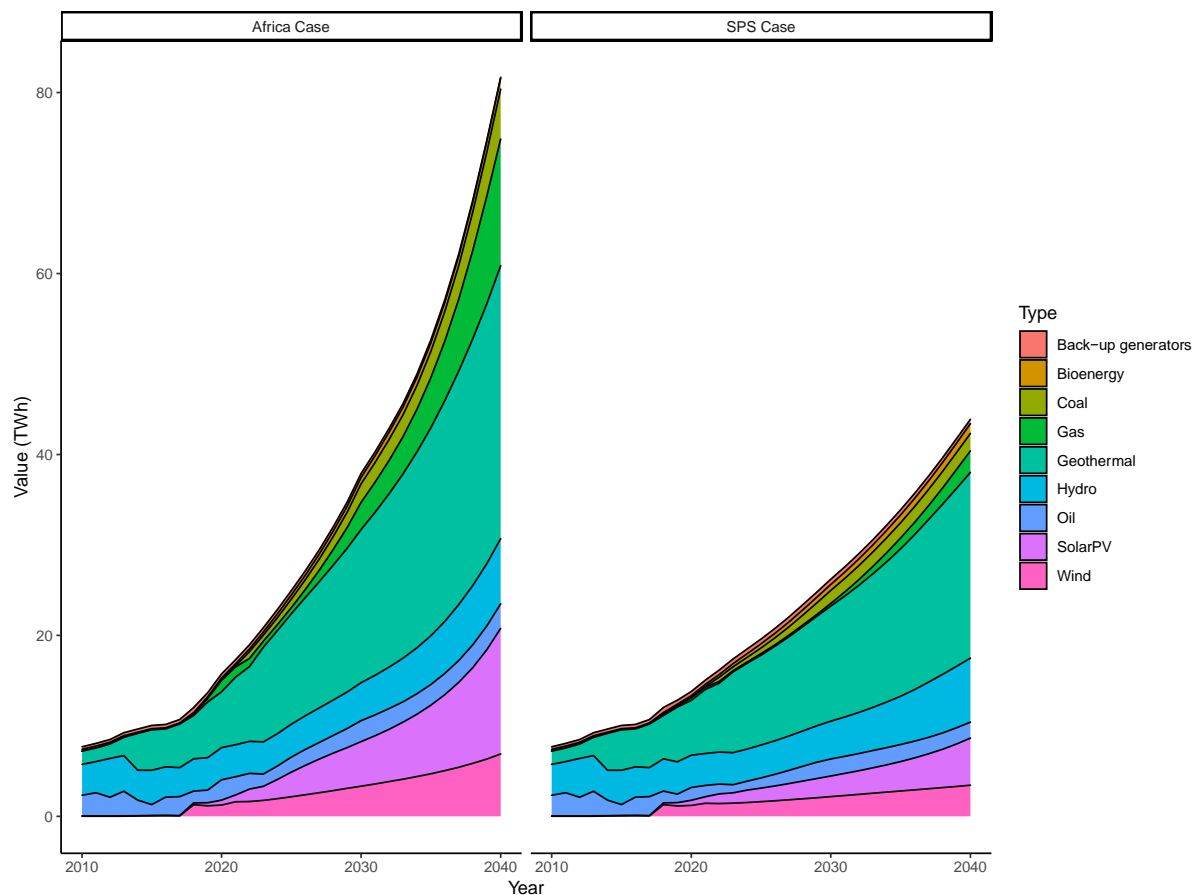


Figure 2: Kenya electricity generation by technology in the Stated Policies Scenario (SPS) and Africa Case Scenario, 2010-2040 [3].

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