

# Challenges for Probabilistic Generation Adequacy Assessment in Sub-Saharan Africa



# Challenges for Probabilistic Generation Adequacy Assessment in Sub-Saharan Africa

Gruffudd Edwards and Chris Dent
School of Mathematics
University of Edinburgh
Edinburgh, UK, EH9 3FD
Email: gruffudd.edwards@gmail.com

Neal Wade
School of Electrical and Electronic Engineering
Newcastle University
Newcastle, UK, NE1 7RU
Email: Neal.Wade@newcastle.ac.uk

***Abstract*—This paper explores the need for, and challenges associated with the probabilistic assessment of the generation adequacy of power systems in Sub-Saharan Africa, using Kenya and Ghana as examples. Some relevant distinctive characteristics of these systems are discussed, and previous work in this area is reviewed. Illustrative data analysis for the future Kenyan system is presented, exploring the temporal relationship between the wind power resource, demand, and the hydro power resource – to provide insight on the potential contribution of large wind projects to generation adequacy.**

## I. Introduction

Many countries in the Sub-Saharan Africa (SSA) region are experiencing very rapid changes in the size and generation mix of their power systems, due to rapid economic and population growth. For example, the region experienced a 45% increase in annual energy consumption between the years 2000–2014 [1], with the growth in some countries much higher. Organisations such as the World Bank, Western governments and private developers – in addition to many African leaders – are keen to see high penetrations of variable renewable (VR) generation within the emerging systems, as evidenced by e.g. [2].

This paper studies generation capacity adequacy assessment in SSA countries, and considers the power systems of Kenya and Ghana as examples. In those countries, detailed and necessarily ambitious plans and scenarios have been developed for generation capacity expansion, and those plans are largely being successfully executed. However, no probabilistic capacity adequacy study has yet been conducted for the planned future systems, although the need for such a study for Ghana was identified in [3].

Indeed, adequacy assessment in SSA countries – and indeed in the developing world generally – has received very little attention in the academic literature, or in institutional reports. This paper will identify the main technical challenges for SSA countries, review the relevant literature, and present some illustrative numerical examples for wind generation in Kenya.

## II. Distinctive Characteristics of SSA Power Systems in Adequacy Assessment

This section presents some differences between the chosen SSA power system examples and those in developed countries, pertinent to generation adequacy assessment. In the SSA systems:

- Energy constraints have a strong negative impact on adequacy, so detailed assessment must involve sequential simulation, with dispatch considered, rather than only the mechanical availability of generators. This is true largely due to a combination of the historical dominance of hydro power and the very significant inter-annual variability of the hydro resource [3]. The governments of both countries are therefore attempting to reduce the penetration of large hydro in their generation mix.
- Energy constraints may also apply, to some extent, to thermal generators - due to fuel supply problems, such as restricted supply of gas from Nigeria to Ghana [4].
- Load shedding is common [4], both planned and unplanned, due to operational difficulties and the unreliable nature of distribution networks, in addition to insufficient transmission and generation capacity.
- Demand therefore cannot be equated with dispatch, partially due to the load shedding, but also due to suppressed demand, of different types. At the one end, some households or businesses are forced to consume less when prices are higher; at the other end is missed opportunities for investment in productive activity due to the persistent unreliability of the system [3] [8].

## III. Previous Work and Challenges for Specific Aspects of Adequacy Assessment

### A. Accurate Demand Forecasting

Demand growth in the Kenya and Ghana power systems has been very rapid during recent years, a trend that is set to continue into the future. For example, Kenya's *Least Cost Development Plan* for 2011–2033 [8] has their central forecast for peak demand rising from 1,606 MW in 2013 to 21,075MW by 2033. The forecast has much associated uncertainty, with the feasible 'low growth' forecast being roughly 50% lower than the central forecast by 2033, while the 'high growth' forecast is roughly 50% higher.

The forecasts of [8], use macroeconomic analysis to make their predictions, as is typical globally. The limitations of relying solely on such 'bottom-up' analysis for rapidly developing systems is highlighted by a research article by the Wold Bank [9]. The authors point out that accurate demand estimates

depend on realistic estimates of disaggregated demand, including suppressed demand. Successful forecasts, they state, must account for physical, financial, and institutional constraints and make use of detailed demographic data and distribution network planning.

### B. Thermal Generation

The main challenge associated with modelling thermal generation is the relative sparsity of data, particularly in the public domain, relating to their reliability in an SSA context – for example how quickly faults might be fixed. This is particularly true for Kenya, where much of the new generation being built and planned is geothermal. There is also uncertainty about the extent to which their fuel supply can be modelled as reliable, as previously mentioned.

### C. Hydro Generation

Rapid growth has meant that the demands made of hydro reservoirs are greater than they can sustain, and levels regularly fall below the minimum for operation. Accounting for the complex meteorology is challenging, particularly given the uncertainties of climate change. Modelling joint availabilities for the hydro and VR resources is complex but essential, which motivates the exploration of temporal relationships between the hydro and wind resources in Kenya in section IV. In Ghana, plans are in place to significantly increase small and micro hydro capacity, which presents further modelling challenges [5].

### D. Variable Renewable Generation

Interest in photovoltaic (PV) solar energy is strong in both countries, but particularly Ghana. Provisional licences have been granted by Ghana's Energy Commission to solar projects there with a total capacity of 2,748.5MW, despite the peak power dispatch in 2015 being only 2,118MW. Kenya is in the process of dramatically increasing it's wind generation capacity, through large and high profile projects such as 310MW at Lake Turkana.

Modelling the output of grid-scale PV projects has an advantage over wind projects in that meteorological stations, introduced for agriculture, are typically in locations where the solar resource is more closely matched to that found at prospective project locations. However, meteorological station insolation data is not ideal for modelling purposes, as their measures of cloud cover may not reflect what matters for PV generation. Also, modelling the output of many small PV systems would require some challenging spatio-temporal statistical modelling.

Most work to date on variable renewable energy generation in Kenya and Ghana has been concerned with assessing and characterising the wind and solar resource, e.g. assessment of the wind resource along the coast of Ghana in [10]. This paper is the first to explicitly consider their contribution from a system perspective.

Solar generators would make very little direct contribution to the generation adequacy of the Kenyan system, since the daily demand profile has a distinct peak during dark evening hours, as shown in fig. 2. In Ghana, the profile is much flatter – although an evening peak is present [3], so solar could make somewhat more of a contribution. In both cases, however, solar could potentially make an indirect contribution during times of drought by reducing the demand for hydro power during daylight hours [11].

The Ghana Energy Commission has also granted a provisional licence for a 1000MW wave energy project, however, given the immaturity of this technology it seems unlikely that this project will be developed in the foreseeable future.

### E. Whole System Adequacy Assessment

The acquisition and model development work required for a full probabilistic generation adequacy assessment of the Kenya and Ghana systems would be very significant, particularly for the radically different systems predicted to exist even in the near future.

A deterministic reliability assessment for Ghana was completed in 2010 [3], which covered generation, transmission and distribution. A Masters thesis by Rose [11] was concerned with calculating the economic value of various penetrations of solar generation to Kenya's power system, achieved by developing a dispatch optimisation model. Although the analysis is deterministic, use is made of historical resource time series, and risk metrics were derived. Extension of this work to include stochastic optimisation would be of great value, albeit very computationally expensive.

Due to the load shedding and suppressed demand, it can be argued that traditional adequacy metrics – particularly the Loss of Load Expectation, might not be the most appropriate for SSA countries. After all, it might be the case that the full demand is never entirely met. One alternative might be quantiles for the energy that can be served for each hour on a typical weekday, conditional on some target dispatch.

## IV. Exemplar: Wind Energy in Kenya

### A. The Scenario

This section explores the potential contribution of large wind energy projects to generation adequacy in the Kenyan power system. It does so by examining temporal relationships between wind resource availability and demand, and also – on a coarse resolution – between the wind and hydro resources. With the data available sparse, strong modelling assumptions are necessary, however all major modelling components were re-run with contrasting assumptions, to assess the sensitivity of results to the assumptions made.

We consider a scenario for the Kenyan system circa 2020, in which the peak power demand is 4GW and there is 925.5 MW of installed wind capacity. The wind projects in this scenario and their capacities (based on August 2016 plans) are: Lake Turkana - 310 MW, Meru - 400 MW, Kajiado - 100 MW, Ngong Hills - 25.5 MW, Lamu - 90 MW. The peak demand value of 4GW in 2020 corresponds approximately to the best central forecast reported in [8].

### B. Relationships between Wind Power and Demand

A 22 year, hourly resolution time series of modelled wind generation was derived from wind speed series recorded at 5 meteorological stations in Kenya (Dagoretti, Lamu, Makindu, Marsabit, Meru), between 1980–2001. Each series acted as a proxy for the speeds at one of the project locations, with linear and power transformations applied so that the series matched estimated values of mean wind speed and mean cubed wind speed at the project sites, as given by a wind resource map of Kenya [6]. Diurnal patterns in mean were removed from the series before matching with the map values. The reason is that the diurnal patterns at hub height are unknown, while it is known that such patterns diminish significantly with height in some climates [7]. The transformed wind speeds were converted to normalised powers using a large-area wind farm power curve, before being scaled according to the capacities of the planned projects, and finally summed. This modelling approach is referred to here as the 'base model' for wind.

A year-long, hourly resolution time series of generation dispatch was obtained from the system operator, Kenya Light and Power. The dispatch is taken as a proxy for demand here, after being linearly scaled-up to a peak level of 4GW. The validity of such a simple transformation is supported by the fact that the demand load factor remains almost unchanged in the forecasts of [8]. There is no discernible annual reasonality in the demand trace, and since there is little demand on the system for space heating and cooling, there is no obvious machanism for demand to vary from year to year given constant underlying patterns.

The fairly small annual seasonality in wind power is presented in fig. 1, which shows average values for the 22 year sample. The figure also demonstrates roughly the season to which each month belongs, and presents average monthly precipitation for a single location, Makuyu, obtained from [12]. As is discussed below, the latter is taken in this work as a proxy for the monthly inflow into the Masinga reservoir, the largest hydro power scheme in terms of energy. Figure 1 demonstrates that the relative availability of the wind resource during the 'hot dry' month is rather disappointing, but it is good during the longer 'cool dry' season.

Since removal of the diurnal profile from the wind speeds in the base model is one of a number of plausible ways of dealing with this particular uncertainty, it is worth considering the typical relationship between wind power and demand for a wind model variant where the diurnal pattern remains. This is presented in fig. 2, which shows that the diurnal pattern in wind power is significant, but not very pronounced. Further, the profile peaks are not coincident, with wind power peaking during the hottest hours of the afternoon, while demand peaks during dark evening hours. Thus, it is unlikely that conclusions about the potential contribution of wind to capacity adequacy are very sensitive to assumptions about the diurnal variability of wind.

Figures 3–5 present duration curves for demand net wind generation. These were obtained by repeating the scaled-up

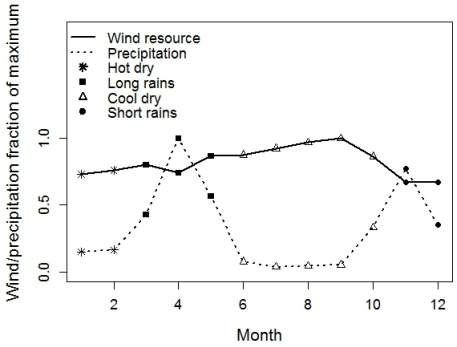


Fig. 1. Normalized monthly profiles of modelled wind resource (base model, Kenya 4GW peak scenario) and Masinga reservoir inflow. Four Kenyan seasons indicated.

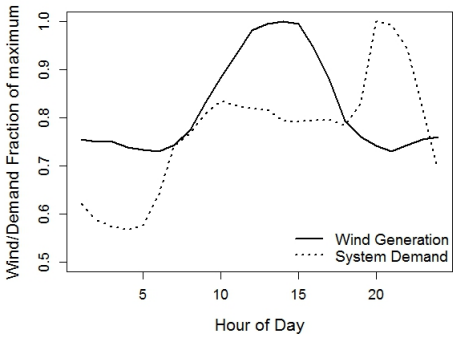


Fig. 2. Normalized diurnal profiles of wind resource – assuming variability preserved – and demand, 4GW peak Kenya scenario

demand trace 22 times and subtracting the wind power trace. Figure 3 and fig. 4 present results for the full range of net demand values observed in the series, and use a linear and log scale for the number of hours where net demand is exceeded, respectively.

Results using the base model of wind power are contrasted with those where there is no wind generation, and also with 2 variants of the wind power model. The 'linear scaling' variant has wind speeds transformed using linear re-scaling only; while the 'single turbine' variant adopts the power curve of a single turbine only. Results for the self-explanatory 'keep diurnal' variant were also calculated, but are omitted from the figure since they are indistinguishable from the base case, confirming the observation above. Indeed, the results are, generally, strikingly non-sensitive to the model variants. One partial exception is that results are moderately sensitive to the choice of power curve for peak net demand levels.

Results were also calculated for a 2024 scenario (based on [8], 2013 update), where peak demand has increased to 6GW, and the total wind power capacity has increased by the same proportion. However, 2 scenario variants were considered, exploring the impact of spatial smoothing: (i) 4

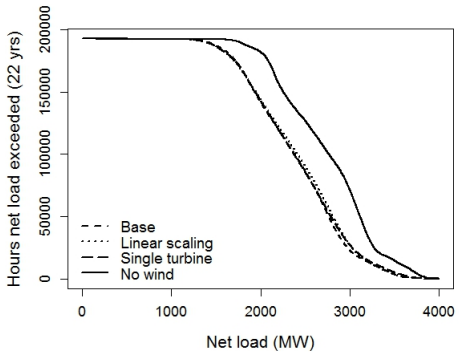


Fig. 3. Modelled duration curve for demand net wind generation (base model), 4GW peak Kenya scenario, linear scale.

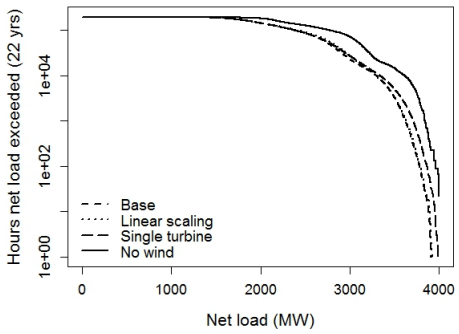


Fig. 4. Modelled duration curve for demand net wind generation (base model), 4GW peak Kenya scenario, log scale.

additional projects have been built – the 'additional locations' model variant; (ii) only the same 5 projects exist, but the capacity of each has increased by 50%. It was found, rather surprisingly, that there is generally very little difference in the duration curves for these variants, with the only real difference occurring at the high net demand demand extreme. These peak demand results are presented in fig. 5.

### *C. Relationships between the Wind Power and Hydro Resources*

Analysis of relationships between the wind and hydro power resources involves monthly resolution data for two reasons: (i) finer resolution data on the hydro resource is harder to obtain, and (ii) we do not know what the operating strategy for hydro power might be in the chosen scenario, in particular the extent to which close coordination between wind projects and hydro reservoirs might be achievable.

Kenya has many hydro reservoir and run of river schemes, including a cascading scheme of reservoirs. This illustrative analysis requires a single variable that summarises the hydrological resource at a given time, and water inflow to the Masinga reservoir was chosen. As explained in [13], this variable is suitable on account of the fact that the Masinga

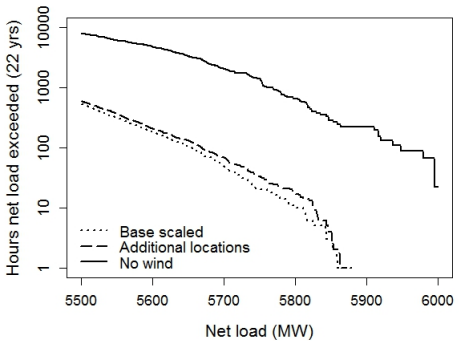


Fig. 5. Modelled duration curve for demand net wind generation (base model), peak demand region, log scale, 2 scenarios for 6GW peak in Kenya.

dam's essential roles are to regulate water flow into subsequent dams, particularly during the dry seasons, as well as preventing flooding. While downstream reservoirs have much greater power capacities, and have other sources of river inflows apart from Masinga discharge, during the dry season these are insufficient for effective operation. Net inflow here means gross inflow minus evaporation and spillage, and annual values are provided in [13] for the period 1982–2001.

In order to move to monthly resolution data, precipitation data must be used, after calibration to the annual inflow series. Use was made of 2 data sources, each associated with a model variant – again for sensitivity analysis.

One source is a precipitation time series for an unspecified location in Kenya, obtained from a World Bank climate data repository [14], which also spans the period 1982–2001. The assumption was made that, for a given year, the relative contribution from each month to the annual Masinga dam inflow was identical to the relative contribution of each month to the total annual precipitation in the World Bank data, i.e. there is 100% correlation across the county with regard to this aspect.

The opposite modelling assumption, included to assess sensitivity, is that there is no correlation across space with regard to the relative contribution from each month. As a result, the best way of constructing a monthly resolution series is to take a long term average profile of precipitation, and scale it to match the total inflow for each year. This was done using the profile obtained from [12], since Makuyu is located in the hills feeding the Masinga reservoir. The contrasting assumptions are labelled model 1 and 2, respectively.

Figure 6 presents 20-year series for wind generation and the model 1 inflow. The plot shows that the size of the wet season 'spikes' in the inflow series exhibit distinct but complex clustering behaviour. The wind power series also possesses clear seasonality, but much less pronounced than inflow; also there are very low frequency trends on a time scale of decades. The resources therefore appear to be somewhat complementary, although the relationship requires further elucidation. For model 2, the inflow series displays the same characteristics, but

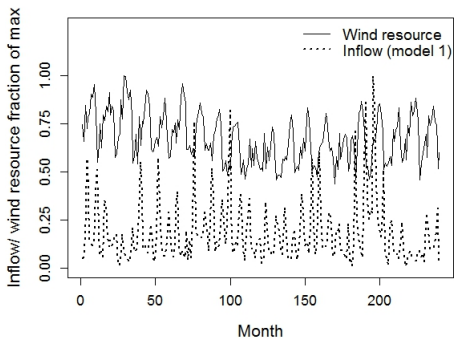


Fig. 6. Normalized 20 year series, monthly resolution, for the modelled wind resource (base model), 4GW peak Kenya scenario, and Masinga reservoir inflow (model 1).

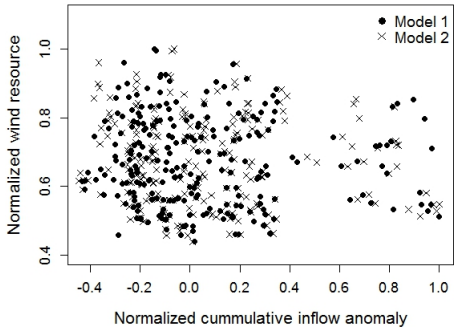


Fig. 7. Relationship between wind resource (base model, 4GW peak Kenya scenario) and temporally accumulated Masinga inflow anomalies, both models.

the exact location and amplitude of spikes within the clusters are are occasionally quite different.

Additional clarity regarding the extent of complimentarity between the resources is provided by a scatter plot in fig. 7. The hydrology data in the figure is not the raw inflow series, rather the accumulation over time of anomalies from the average behaviour. Very roughly, a large positive cumulative anomaly means the dams are likely full, while a large negative value implies they are likely empty. The figure shows that there is not a strong relationship between the 2 variables.

However, many of the strongest months for the wind resource occur when the anomaly is negative, implying that wind can make an useful contribution. It is also worth noting that the monthly wind load factors are consistanly high, with the worst month being ¿ 40% of the highest. It is true that during the most extreme anomaly values, the wind resource is disappointing, but the dataset is too small to draw any conclusions from this – a metrorological explanation would be required. The consistency of the rough shape of the scatter plot across the 2 models indicates that results are not sensitive to this aspect of the modelling.

## V. Conclusion

It was seen that there is a strong need for capacity adequacy assessment for the power systems of Kenya and Ghana, which are both growing in size very rapidly, and are likely to see a large penetration of variable renewable generation. There are however many technical challenges to be addressed before such assessments can be completed. This paper has explored temporal relationships between the wind power resource and demand, and between the wind and hydro power resources for near-future scenarios of the Kenyan system. Results inicate that there is some complimentarity between these variables, and as such the planned large wind projects might be able to contribute significantly to generation adequacy. Due to limitations on the data currently available, strong assumptions were necessary in order to produce results, however these preliminary conclusions demonstrate that there is value in further, more detailed studies, including more resource devoted to data gathering.

## Acknowledgment

The authors would like to thank our partners in the Green Growth Diagnostics for Africa Project, along with interviewees in Kenya and Ghana wh kindly gave their time.

## References

[1] World Energy Outlook, *Africa Enegy Outlook – Executive Summary*, International Energy Agency, 2014. Available: https://www.iea.org/publications/freepublications/publication/AEO_ES_English.pdf

[2] *Summary of the AREI Framework Document and Action Plan*, Africa Renewable Energy Initiative, 2015. Available: http://www.arei.org/wp-content/uploads/2016/09/AREI-Summary-english_web.pdf

[3] Power Systems Energy Consulting (for GRIDCO), *Ghana Wholesale Power Reliability Assessment 2010*, 2010. Available: http://www.gridcogh.com/media/photos/forms/rel-assessment/2010_GRIDCo_Reliability_Assessment_Report.pdf

[4] Volta River Authority, *Fifty Third Annual Report and Accounts 2014*, 2015. Available: http://www.vra.com/resources/annual_reports/2014\%20Annual\%20Report.pdf

[5] Ghana Energy Commission, *2016 Energy (Supply and Demand) Outlook for Ghana*, 2016. Available: http://energycom.gov.gh/files/Energy\%20Commission\%20-\%202016Energy\20Outlook\%20for\%20Ghana_final.pdf

[6] D. Theuri, *Solar and Wind Energy Resource Assessment – Kenya Country Report*. Available: http://en.openei.org/datasets/dataset/solar-and-wind-energy-resource-assessment-kenya-country-report

[7] A. Sturt and G. Strbac, *A times series model for the aggregate GB wind output circa 2030*, RPG 2011, IET Conference on, Edinburgh, 2011, pp. 1-6.

[8] *Updated least Cost Power Development Plan, Study Period: 2011 – 2031*, also *Study Period 2013 – 33*. Republic of Kenya Energy Regulatory Commission, 2013. Available: http://erc.go.ke

[9] D. Chattopadhyay et al., *Planning for Electricity Access*, Live Wire vol. 35, World Bank, 2014. Available: https://openknowledge.worldbank.org/handle/10986/20596

[10] M.S. Adaramola et al., *Assessment of wind power generation along the coast of Ghana*, Energy Conversion and Management, vol. 77, pp. 61–69, Elsevier, 2014.

[11] A.M. Rose, *Prospects for Grid-Connested Solar PV in Kenya*, Masters Thesis, Massachusets Institute of Technology, 2013.

[12] *Climate Data*. Available: http://en.climate-data.org/location/927015/

[13] M. Bunyasi et al., *Vulnerability of Hydro-Electric Energy Resources in Kenya Due to Climate Change Effects: The Case of the Seven Forks Project*. J. Agr. and Env. Sciences, vol. 1, pp. 36-49, 2012.

[14] The World Bank Group, *Climate Change Knowledge Portal*. Available: http://sdwebx.worldbank.org/climateportal/index.cfm?page=country_historical_climate&ThisCCode=KEN