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GREEN POWER FOR AFRICA: OVERCOMING THE MAIN CONSTRAINTS

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Assessing the Potential Impact of Grid-Scale Variable Renewable Energy on the Reliability of Electricity Supply in Kenya*

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Abstract Securing a sufficient supply of reliable and affordable electricity is a major challenge for countries in sub-Saharan Africa (SSA), due to low current access levels, and rapid population and economic growth. This article will review application and technical modelling issues associated with generation adequacy assessment (i.e. assessing the risk of available generation being less than demand) in the context of SSA countries with significant capacities of renewable energy, with Kenya as the main case study. One major challenge in performing such studies in SSA is often availability of the necessary data on renewable resource and demand – the article will further demonstrate how useful information may be gained on the extent to which wind and hydro energy resources complement each other in Kenya, in the context of limited data availability.

Keywords: electricity, renewable, energy, reliability, Africa, Kenya, grid, adequacy, risk, demand, resource.

1 Introduction

Securing a sufficient supply of reliable and affordable electricity is a huge challenge for countries in sub-Saharan Africa (SSA). Many countries in the region are experiencing rapid increases in the size of their populations, and even more rapid growth in their economies (World Bank Group 2017a). As a result, the region experienced a 45 per cent increase in annual energy consumption during 2000–12 (World Energy Outlook 2014), with the growth in some countries much higher.

In 2009, the World Bank stated (Eberhard *et al.* 2008) that SSA was amid a power crisis characterised by unreliable supplies, largely due to insufficient generating capacity, high prices, and often higher costs. Indeed, in 2008, the World Bank's Africa Infrastructure Country Diagnostic (AICD) project (Eberhard *et al.* 2011) calculated that while there was a need for 7,000MW of additional power generation capacity

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to be installed in SSA countries each year, the total installed in prior years was only one seventh of that. This is a costly problem for SSA countries (Deloitte 2015), with the AICD project calculating in 2009 (Rosnes and Vennemo 2009) that the region would have to spend roughly 4 per cent of gross domestic product (GDP) annually on power sector investments to meet the demands of economic development, keep pace with population growth, and increase energy access. Despite major efforts towards increasing the reach of electricity networks in recent years, the SSA average rate of access in 2014 was only 35 per cent. Access rates are much lower in some countries – for example, Chad's is only 4 per cent, while Ethiopia's is 25 per cent, with 73 million people without access.

Thus, building very significant generation capacity is both essential and inevitable in the near future. For many reasons – including location, maturity of technology, and speed of building – traditional fossil fuel power plants are well suited to fill the gap. However, many stakeholders in the SSA power sector are keen to see these power systems largely avoid such a highly polluting stage. Hydro power is already a major component of SSA's generation fleet, and plentiful resource means that more reservoirs will likely be built. However, in some cases the potential for economically and politically viable development is insufficient to meet the growing demand alone. There is therefore a strong desire to see high penetrations of variable renewable generation (VG) within many systems (AREI 2015).

The power systems of SSA countries generally face four fundamental and interrelated problems (although the extent of each varies considerably between countries):[4] (i) unreliable supply due to insufficient (functioning) generation capacity to meet all of the demand on the system; (ii) unreliable supply due to failing or insufficient power distribution infrastructure; (iii) very large percentages of the population without access to the grid; (iv) prices that are too high for the majority of current and potential new customers but still below cost recovery. It stands to reason that when assessing the value of proposed large-capacity VG projects in a SSA power system, the relevant policymakers and stakeholders should possess as much insight as is reasonably possible on the extent to which they might alleviate these problems. Or, if VG projects are proposed specifically to deal with one or two of these problems, rigorous assessment should be available on their impact on the others. It is immediately evident that to truly assess impacts on these problems, especially given the complex interrelationships between them, a thorough interdisciplinary approach is needed.

This article will explore in detail impacts of VG on problem number (i) – an area of analysis known as capacity adequacy assessment. Indeed, the International Energy Agency's 'Energy Outlook' summary for 2016 (World Bank Group 2017a) states that the deployment of renewable generation already plays an important role in the mitigation of traditional energy security concerns, by moderating oil and gas imports.

However, they warn, rising shares of VG puts the reliability of electricity supply under pressure in a different way, due to their unpredictable and intermittent nature. Despite the hugely ambitious scale of current and near-future planned VG investments, there has been almost no system-level analysis of the reliability impacts of grid-scale VG in SSA countries, either from the academic community or from government and industry.

The ability of the generators within a power system to consistently meet the demands made of them by customers is known as the system's generation adequacy. It may be captured through a variety of metrics, with the most meaningful being risk-based and probabilistic in nature. A popular example is the expected value for the number of periods (e.g. 30-minute intervals) within a year where the available generation is insufficient to fully meet demand – known as the loss of load expectation (LOLE). Unfortunately, there has been very little research on the potential contribution of VG to the generation adequacy of SSA power systems. Indeed, detailed risk-based assessment of generation adequacy in developing countries in general has rarely been addressed in the academic and industrial literature, an exception being the work of Billinton and Pandey *et al.* in several publications, for example Billinton *et al.* (1995).

This is not to say that it is unknown whether the addition of a large VG project might in fact decrease the reliability of an SSA power system. Adding capacity to a system cannot decrease its generation adequacy, although operational constraints might limit the adequacy contribution of VG capacity. While operational problems caused by VG might be mitigated through curtailment (i.e. the system not taking the full available output of VG at times when this is challenging), this clearly reduces the contribution VG can make and increases unit cost. Understanding precisely the extent to which this and other technical issues limit the potential contribution of VG to capacity adequacy in the new context of SSA power systems is challenging, as is discussed in Section 3 of this article, and is currently beyond the scope of analysis performed by SSA power system operators and regulators.[5]

Despite the technical barriers to conducting full and rigorous capacity adequacy assessments to assess the contribution of large-capacity VG projects to SSA capacity adequacy, it is possible for policymakers and other stakeholders to conduct much simpler analysis to gain insight on this vital issue. This article presents an illustrative example of how to conduct such analysis when the data and technical expertise for a complete probabilistic study are not available. This example investigates the wind resource in Kenya, comparing temporal patterns in its (random) availability with patterns in system demand and the (random) availability of the hydrological resource to assess the extent to which the resources complement each other.

Before the presentation of methods, models, and data sources in Section 4 and the presentation of results in Section 5, the article presents the context of the Kenyan power system in Section 2, and provides motivation for the type of analysis conducted in Section 3.

2 Overview of the Kenyan power system

Kenya is situated on the eastern coast of Africa, bisected by the equator. It has a coastal length of 470km (Theuri 2008), varied terrain, and rises to 5,199 metres above sea level. The population is rapidly expanding, having increased from 31 million people in 2000 to 46 million in 2015 (World Bank Group 2017a). The economy has been growing even more rapidly, with GDP increasing from US$12.7 billion in 2000 to US$63.4 billion in 2015 (*ibid*.). In 2010, only 20 per cent of the total population of Kenya, and only about 5 per cent of the rural population had access to electricity, although this situation is rapidly improving (Ogola, Davidsdottir and Fridleifsson 2011).

The peak demand on the system rose from 1,107MW in the 2006–07 financial year to 1,512MW in 2014–15.[6] The energy regulator's central forecast in Republic of Kenya Energy Regulatory Commission (ERC 2013) sees the peak rising from 1,606MW in 2013 to 11,318MW by 2033. The forecast, however, has much associated uncertainty, with the feasible 'low growth' forecast being roughly 50 per cent lower than the central forecast by 2033, while the 'high growth' forecast is roughly 50 per cent higher. A lack of capacity in the past means that there is still a widespread belief that the system is highly unreliable, despite the high level of reliability currently experienced in the cities (except during floods).[7] Many areas of Kenya continue to experience an unreliable supply, however: to a small extent due to insufficient transmission capacity, but mainly due to problems with insufficient distribution capacity and maintenance challenges.

In March 2015, the capacities of the Kenyan power system, grouped by generation type, were as follows: hydropower – 820.6MW; fossil fuels (including emergency power) – 717MW; geothermal – 588MW; wind generation – 25.6MW. While most of the electricity historically generated in Kenya has been from hydropower, it has not supplied most of the country's total *energy* needs – petroleum has, over the years, accounted for about 80 per cent of the country's commercial energy requirements (Oludhe 2008). It is also stated in Oludhe (2008) that the hydropower potential in Kenya in the form of large reservoirs is estimated at about 2,263MW, while the small schemes have a total potential of 3,000MW. Further, there is excellent geothermal resource within the Rift Valley, with the generation potential estimated at over 2,000MW, and geothermal capacity is rapidly being built.

Although equatorial areas are assumed to have poor-to-medium wind resource, Kenya experiences seasonal monsoon winds, and its topographic features have endowed the country with excellent wind resource areas (*ibid*.). Consequently, it is likely that multiple very large wind generation projects, of the order of hundreds of megawatts, will be constructed in the coming years (ERC 2011, 2013). Kenya's equatorial position also means that it has excellent solar resource in many areas, although there are currently no plans for any large-scale solar power projects (ERC 2011).

3 Generation adequacy in Kenya and other SSA countries

Adequacy assessment is concerned with the risk of there being insufficient resources to supply demand in a power system, considering scheduled and unscheduled outages, and availability of renewable resources. Generation adequacy assessment (GAA) studies therefore calculate quantitative measures of the risk of shortfalls, such as the probabilities of shortfalls at different times. Adequacy should not be confused with the flexibility of the system, which is its ability to deploy its resources to respond to changes in net load, both predicted and unpredicted (net load is defined as the remaining system load not served by VG). Neither should adequacy be confused with the security of a power system: its ability to withstand sudden, unexpected disturbances without any serious consequences for the supply to customers.

The generation adequacy of traditional power systems historically has often been measured by reserve margin: the amount by which generation capacity exceeds the projected peak demand, expressed as a percentage of that peak value. This is a simple and static approach that benefits from being very easy to calculate and understand, and is adopted occasionally by system operators in SSA countries, for example Ghana in 2010 (Power Systems Energy Consulting 2010). A much more meaningful approach to GAA is to explicitly consider the risks of generation capacity being insufficient to fully meet demand, using probabilistic methods to model the balance of supply and demand at each point in time.

Since GAA is usually conducted for the mature power systems of developed countries, they are concerned with the frequency and severity of those very rare events when not all demand can be met, referred to as generation shortfall events. Although there are many possible metrics to capture a system's capacity adequacy from this perspective, the most popular are: the loss of load expectation (LOLE), the average duration during a year for which the generation capacity available will be less than the demand); and the expected energy not served (EENS), the average total energy demanded by customers that cannot be delivered by the generators during a year. The assessment of such risk-based metrics is based on a model of the possible random conditions the system might face – including weather outcomes and customer behaviour.

Some LOLE-based analysis informs the long-term planning process for Kenya, as part of the *Least Cost Power Development Plan* methodology (ERC 2011). However, the statistical methodology for converting a set of generators into a risk profile is not as detailed as the international best practice, and makes a strong implicit assumption that risks should be identical on every day of the year (which might not be the case if demand or quality of VG resource varies through the year).

When significant VG capacity is present, accurate results require that the probabilistic method accurately represents spatial relationships in the resource availabilities, for example how often it is windy or calm across the entire region where the VG is located. Where there is significant presence of energy-constrained generation such as hydropower, it is also vital to capture temporal relationships in the resource availabilities. This is the case in Kenya, due to a combination of the historical dominance of hydropower and the very significant inter-annual variability of the hydrological resource – i.e. the Kenyan system has experienced serious capacity problems in the past following a series of dry years.

This problem is being effectively mitigated by the Kenyan government by ensuring that hydropower makes up a smaller percentage of the generation mix as the system grows. However, the percentage certainly remains high enough that rigorous capacity adequacy assessment must consider the operational decisions of hydro generation. Energy constraints also typically apply, to some extent, to thermal generators in SSA countries. For instance, this is the case in Ghana, where the supply of natural gas from neighbouring Nigeria has been very unreliable (Power Systems Energy Consulting 2010), among other problems. Kenya is, however, rather unusual in that its extensive geothermal capacity renders it less vulnerable to fuel supply issues.

It was stated in the introduction that the main contribution of this article is to provide an illustrative example of a desktop study that provides insight into the potential contribution of VG to the reliability of an SSA power system. The full probabilistic generation adequacy assessments described in this section go beyond such desktop studies; however, presenting some background knowledge about full studies motivates desirable features of simpler analysis. A useful desktop study should reveal the salient aspects of spatial relationships for the VG resource availability, as well as relationships between temporal patterns in the resource availability, system demand, and the hydrological resource availability. In simpler terms, it is vital to examine the extent to which wind generation can provide power when demand is high and the power available from hydropower is compromised by drought.

4 Illustrative example: the Kenya model

This section proceeds with the main objective of the article: to present an illustrative example of a desktop study of the VG resource in an SSA country, designed to gain insight about the ability of associated VG capacity to increase the power system's capacity adequacy. The chosen example 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, also between the wind and hydropower resources, on a coarse resolution. This section presents the data sources available and sets up the models and Kenyan system scenarios used in the analysis.

4.1 The Kenyan power system scenario

We adopt two simple scenarios for the Kenyan power system in the relatively near future, taken from the 2013–33 Least Cost Power Development Plan (LCPDP) (Ummel and Fant 2014). One scenario has the peak power demand of the system as 4,000MW (4GW), which is close to the forecasted demand of 3,939MW in the year 2022. The second scenario has the peak demand as 6,000MW (6GW) – close to the forecasted demand of 6,147MW in 2026. In the 4GW scenario, there is 925.5MW of installed wind capacity. The wind projects included in this scenario deviate somewhat from the LCPDP, and rather includes those projects that seemed most likely to be built at the time of writing (August 2016), based on their legal and financial status. They are: Lake Turkana – 310MW; Meru – 400MW; Kajiado – 100MW; Ngong Hills – 25.5MW; and Lamu – 90MW. This is referred to as the *Original* wind capacity scenario.

For the 6GW demand scenario, we assume that wind capacity has grown proportionally, i.e. increased by 50 per cent to 1,388.25MW. We consider two scenarios for the spatial distribution of wind capacity in this case: (i) the *Additional Locations* variant, where four additional projects have been built – in areas of strong wind resource where, according to online news reports, some interest has been expressed in developing projects; (ii) the *Increased Capacity* variant, where only the same five projects exist, but where the capacity of each has been increased. In the *Additional Locations* variant, the additional capacity is distributed equally among the new locations. The motivation for the two scenarios for capacity distribution is that there is uncertainty over the extent of geographical spread of wind projects in Kenya when looking forward to 2026 – and by including scenarios that represent the plausible extremes for this aspect of the modelling, sensitivity to this uncertainty can be quantified.

4.2 The wind power generation model and data available

The general approach adopted involves direct use of historic series to represent possible future output for the chosen scenarios, similarly to several examples in the literature, for example Ummel and Fant (2014). The necessary steps of obtaining time series datasets for the wind power outputs are as follows:

- (W.1) Obtain concurrent time series of wind speeds at locations close to the wind energy projects;
- (W.2) Adjust patterns in average wind speed across hours of the day to reflect values at the turbine hubs, i.e. at the centre of the rotating blades;
- (W.3) Calibrate the series through some mathematical transformation to match any known statistics for the wind resource at the project sites;
- (W.4) Convert the calibrated wind speed series to power output series and add them to establish the total wind power available.

With only limited data available, it is necessary to make many strong modelling assumptions to proceed. Therefore, for each major step listed above, two model variants were developed based on contrasting assumptions, to assess the sensitivity of results to those assumptions.

For step W.1, concurrent and hourly resolution wind speed series were found spanning a period of 22 years, from 1980 to 2001, as provided by the SWERA project (Solar and Wind Energy Resource Assessment) (Theuri 2008; NREL 2017). SWERA is a global project to supply high-quality renewable energy resource information, using a combination of analytical, numerical, and empirical methods to obtain high-resolution VG resource maps for many developing countries. Their modelling activity is also responsible for the complete and quality-assured time series of meteorological recorded data used here. The wind speeds were recorded at nine meteorological stations, each one close to a wind project. The stations for the *Original* and *Increased Capacity* wind project scenarios are Dagoretti, Lamu, Makindu, Marsabit, and Meru. For the *Additional Locations* scenario, the four extra recording stations were Lodwar, Malindi, Narok, and Nyeri. Due to the limited number of suitably located meteorological stations in Kenya, it was not possible to develop contrasting model variants for this step of the wind resource modelling.

A pattern in mean wind speed across hours of the day is known in statistics as diurnal seasonality, and dealing with any such seasonality is step W.2 of the modelling process. It is well established in the literature, for example Sturt and Strbac (2011), that diurnal seasonalities diminish significantly with height in some climates, and it is unlikely that the hub-height of every turbine will match that of the recorded data. As the extent to which diurnal seasonalities diminish with height in Kenya is also unknown, this is a type of uncertainty that must be addressed by contrasting model variants. Thus, in one variant, referred to as the *Base* model, all diurnal seasonalities are removed. In the *Keep Diurnal* model, they remain unchanged.

The next step, W.3, involves calibrating the series to any known statistics of the wind resource at the project locations (rather than reasonably nearby). For the chosen exemplar, there are no statistics available for the wind resource at the precise project locations, but reasonable estimates can be made. The two quantities estimated were the mean wind speed, and the mean of the wind speed cubed – both of which were obtained from the SWERA wind resource map of Kenya (Theuri 2008). The former set of values were extracted directly from the resource maps, by careful visual inspection coupled with coordinates for the modelled wind projects. The mean values of the cubed wind speeds were inferred indirectly from SWERA energy density maps – i.e. the mean kinetic energy contained in $1m^3$ of air, which required estimates of air density at the project sites. These density estimates were obtained using meteorological rules of thumb regarding the reduction of air density with altitude and temperature, both of which are high for the Kenyan locations.

With the two wind speed statistics estimated for each project, the next part of modelling step W.3 was to apply simple mathematical transformations to the wind speed time series, so that they precisely match the mean values, as well as matching the mean cubed values as closely as possible. Two model variants were developed here: the *Base* model that applied both linear and power transformations to the series, and the *Linear Scaling* model that applied only linear transformations. That is, for the *Base* model, if the original wind speed at time t is y_t, the new wind speed is $a \cdot (y_t)^b$, with coefficients a and b established to fit the estimated wind speed statistics as closely as possible. For the *Linear Scaling* variant, the transformation is restricted to only $a \cdot (y_t)$. The coefficients were established by simple trial and error, while restricting b to the physically sensible range of 0.7 to 1.3.

Proceeding to modelling step W.4, the transformed wind speed series were converted to normalised powers, i.e. proportions of the wind project's maximum power, using a function known as a power curve. Being a complex area of considerable modelling uncertainty, two simple contrasting model variants were again developed: the *Single Turbine* variant, where a generic power curve for a typical single wind turbine was used (as may be easily found online). Adopting such a power curve is the equivalent of assuming that all turbines in each project experience the same hourly-averaged wind speeds, i.e. that the geographical spread of the wind project is insufficient to necessitate deviation from the power curve of a single turbine. The *Base* model variant assumes that the geographical spread of each project is significant, and that the single turbine power curve should be considerably smoothed – i.e. reducing the steepest changes in turbine output over a small wind speed range, and extending the range of wind speeds for which some power is produced. This process was conducted in accordance with several examples in the literature. Finally, the normalised power series from both variants were scaled by the capacities of the planned projects, and summed.

Although the three branching points in the wind power modelling mean that there are eight variants for the overall process, we did not investigate all of these, since we are interested in the sensitivity surrounding each modelling assumption individually. Thus, the overall *Base* model is that in which the *Base* variant was chosen at each stage, while for example the overall *Single Turbine* model is one where the *Base* variant was chosen in steps W.2 and W.3, but the *Single Turbine* alternative was chosen in step W.4.

4.3 The demand model

A year-long, hourly resolution time series of generation dispatch (i.e. total power generated) was obtained from Kenya Light and Power, the country's electricity retailer and distributer. The series is taken as a proxy for temporal patterns of demand in both system scenarios, after being linearly scaled up to a peak level of 4GW and 6GW, respectively. The validity of such a simple transformation is supported somewhat by the fact that in the LCPDP forecasts, the demand load factor – the energy consumed in a year divided by the energy consumed if the demand were constantly at its peak level – remains almost unchanged. It is interesting to note that there is no discernible pattern in the demand across weeks of the year (i.e. annual seasonality), although there are obviously diurnal and weekly seasonalities.

Since there is little demand on the system for space heating and cooling, there is no obvious mechanism for demand to vary from year to year given constant underlying patterns, unlike the UK, for example, so there is little need to explicitly model this uncertainty.

4.4 The hydrological resource model

The analysis of relationships between the wind and hydrological resources presented in this article is limited to monthly resolution data, for two reasons: (i) finer resolution data on the hydropower resource is difficult to obtain, and (ii) we cannot be certain what the operating strategy for hydropower might be in the scenarios, particularly the extent to which close coordination between wind projects and hydropower reservoirs might be achievable.

Kenya has many hydropower reservoir and run-of-river schemes, including a cascade scheme of large reservoirs in a single river basin. As the analysis presented in this article aims to be illustrative and transparent, a single variable is required that can represent, in a reasonable way, the hydrological resource available. Water flow into the Masinga reservoir was chosen since, as explained in Bunyasi (2012), the Masinga dam's roles are to regulate water flow into subsequent dams, particularly during the dry seasons, as well as to prevent flooding. While downstream reservoirs have much greater power capacities, Masinga dominates in terms of energy capacity. The downstream reservoirs have other sources of river inflows apart from Masinga discharge, but during the dry season – when capacity adequacy is critical – these are insufficient for operation. The quantity modelled here is the net inflow, i.e. the gross inflow minus evaporation and spillage, and *annually averaged* values are provided in Bunyasi (2012) for the period 1982–2011.

To obtain monthly (rather than annual) resolution time series, data limitations mean that precipitation must be used as a proxy variable, following calibration. Use was made of two such data sources, and each is associated with a contrasting model variant, again for sensitivity analysis. The first model variant, labelled *Perfect Correlation*, uses a monthly-resolution precipitation time series for an unspecified location in Kenya, obtained from the World Bank's climate data repository (World Bank Group 2017b) spanning the coincident period 1982–2011. The modelling assumption made is that the relative contribution from each month to the annual Masinga dam inflow is identical to the relative contribution of each month to the total annual precipitation in the World Bank data. In other words, there is 100 per cent correlation across the county regarding the division of total precipitation between months of the year.

For the contrasting model, labelled *No Correlation*, it is assumed that there is no relationship between the division of total precipitation among the months at the unknown Kenyan location and the inflow to the Masinga dam, so that the World Bank time series is not representative of the inflow to this hydro scheme. Instead, this model variant uses the fixed climatological profile of precipitation for a nearby location, and scales it to match each year's annual net inflows. The climatological profile was obtained from *Climate-Data* (2017) for Makuyu, located in the hills feeding the Masinga reservoir.

For a year where the wet season rains were plentiful, the hydrological resource during the following dry season is likely to be better than if the rains were poor. However, this is not a direct relationship, since the resource available during the dry season depends on the water within the reservoir when that period begins, which might reflect the out-turn of precipitation over several recent years. For example, a wet season with poor rains might have a greater impact on the hydro power resource if it was preceded by a cluster of dry years. For this reason, insight can be gained by working with deviations from the mean pattern of precipitation – referred to here as inflow anomalies. Taking this a step further, we work with cumulative inflow anomalies: for any month t, this is the sum of inflow anomalies from the beginning of the time series period to that month.

A large positive cumulative anomaly implies that the dams are likely to be relatively full, while a large negative value implies that levels are likely to be relatively low, and it is thus adopted as a rough proxy for the resource available. This approach has limitations, particularly lack of knowledge of how full the reservoir was at the beginning of the period; no representation of spilling water due to the level being too high; and not considering the need to maintain minimum flow for ecological or recreational reasons.

5 Results

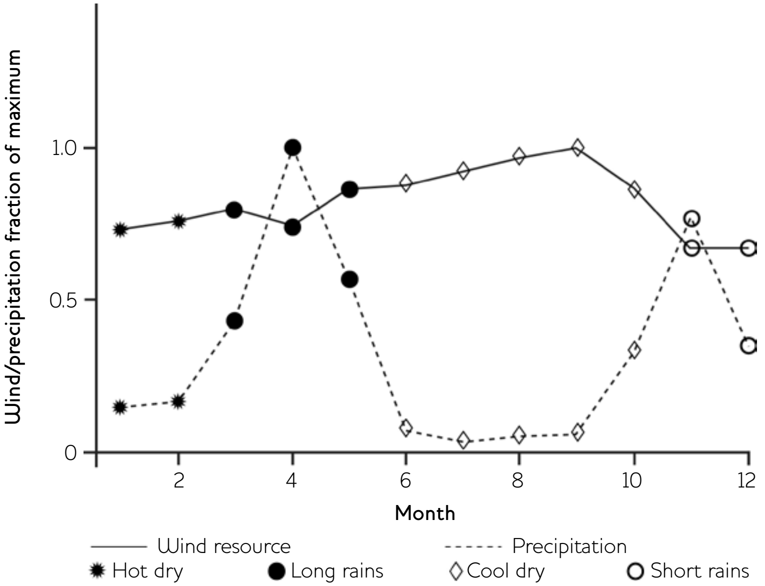
This section presents the results of analysis conducted on the wind energy resource in Kenya, with respect to the potential of wind generation to support capacity adequacy in the Kenyan power system, using the models and scenarios presented in the previous section.

5.1 Seasonal patterns in the mean wind power

The first question investigated was the extent to which the wind varies, on average, between seasons, and whether any such seasonality is complementary to the extremely seasonal nature of the hydrological resource. Since demand does not display annual seasonality, it need not be considered on this temporal resolution. Such questions have received little attention in the literature, with the notable exception of the PhD thesis of Dr Christopher Oludhe (Oludhe 1998).

Figure 1 presents the annual seasonality for the *Original* wind capacity scenario, and the *Base* model for the conversion of wind speeds to power, averaged over the 22 years in the historical sample. It also presents the

Figure 1 **Normalised monthly mean profiles of the modelled wind resource (*Base* model, *Original* scenario) and the hydrological resource (*No Correlation* model)**



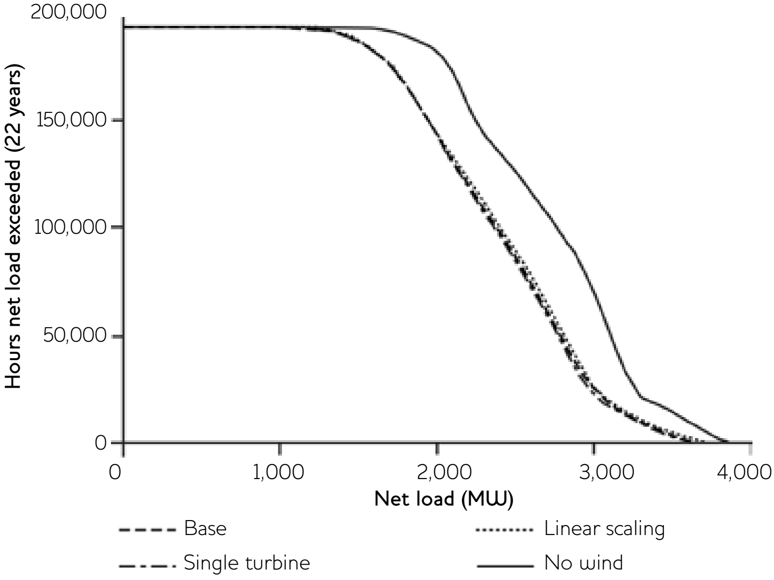
Source Authors' own.

annual seasonality for the hydrological resource, using the *No Correlation* model variant. Values are normalised to facilitate comparison, and the months that roughly correspond to the four seasons experienced by Kenya are indicated. The figure demonstrates that the wind resource is fairly consistent throughout the year, with quite modest seasonality. The relative availability of the resource during the 'hot dry' month is rather disappointing; however, it is good during the longer 'cool dry' season. The plot also demonstrates how distinct the wet and dry seasons are. Very similar relationships are revealed by alternative model and scenario choices.

5.2 Load duration curves for demand net wind

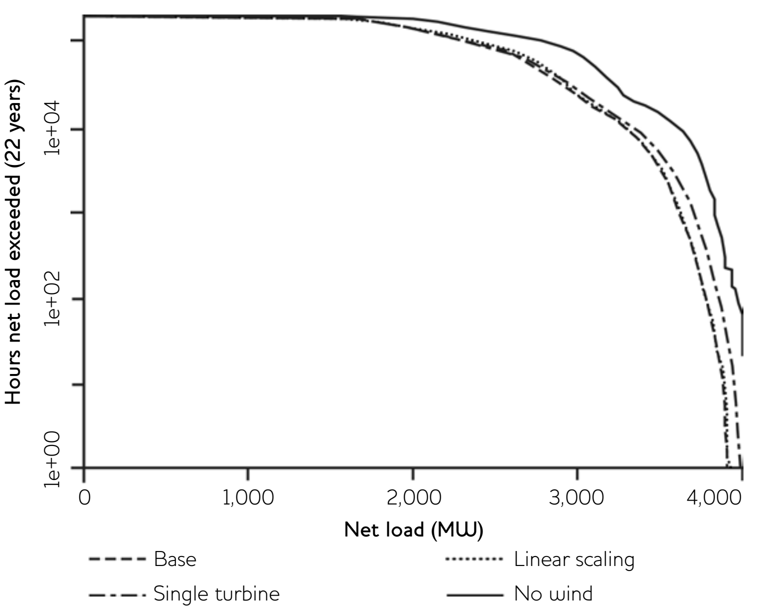
The analysis presented in this section explores the temporal relationship between the wind resource and demand on an hourly resolution. More specifically, it explores the probability distribution of the system demand net of wind generation, and compares this with the distribution of gross demand. The analysis therefore adopts a statistical approach to shed light on the extent to which the wind resource tends to be available to reduce the highest demand values experienced by the system, thus improving its reliability. It also provides some insight on the extent to which wind generation would be able to reduce the depletion of the hydrological resource and/or the consumption of expensive fuel during hours of moderate demand. The probability distributions are presented in the form of load duration curves, which are plots with demand levels plotted on the horizontal axis (either gross or net of wind), and the number of hours where the demand level was exceeded in the modelled series are plotted on the vertical axis. In more technical terms, they are plots of the complementary cumulative distribution function of demand.

Figure 2 **Modelled duration curve for demand net wind generation, *Original* wind capacity scenario, linear scale for hours)**



Source Authors' own.

Figure 3 **Modelled duration curve for demand net wind generation, *Original* wind capacity scenario, log scale for hours)**



Source Authors' own.

Several 22-year time series of net demand were obtained, one for each scenario and model variant. For each scenario, demand-net-wind series were obtained by repeating the scaled-up demand trace 22 times, and subtracting the 22-year-long wind power traces (for each variant). Figure 2 presents results for the *Original* scenario of wind capacity distribution, using a linear scale for the number of hours, while Figure 3 uses a logarithmic scale for this. The number of hours where the demand levels were exceeded in the 22-year series are presented in raw form, rather than as average hours per year, to preserve the true discrete nature of the data.

The plots include curves for the *Base*, *Linear Scaling*, and *Single Turbine* model variants, as well as where no wind capacity is present (i.e. gross demand). The curve for the *Keep Diurnal* variant was omitted from the figures, since they are visually indistinguishable from the base case. In general, the results are 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.

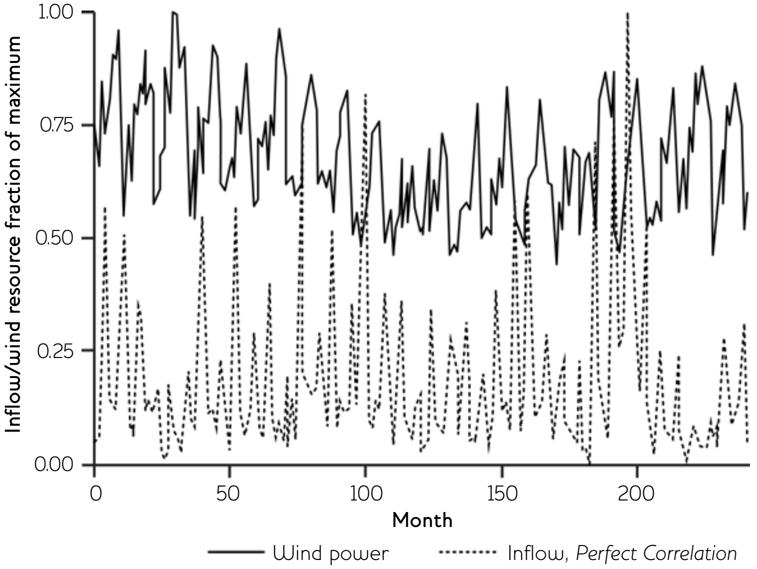
The plots strongly suggest that wind generation can indeed have a significant impact in reducing the frequency of the highest net demand levels, and thus can contribute directly to capacity adequacy assessment. Figure 2 indicates that the impact is particularly evident for demand in the range of about 2,700–3,700MW, while Figure 3 indicates that the impact remains significant right up to the highest possible demands. Figure 2 also seems to support the idea that wind capacity would reduce demand levels throughout a typical day, ensuring that more of the hydrological resource can be reserved for when it is most needed – although there are many constraints, both technical and non-technical that might limit the extent to which this is possible.

Duration curves were also plotted for the two other wind capacity distributions, *Increased Capacity* and *Additional Locations*, for the *Base* model variant, to examine sensitivity to the number of locations. It was found, rather surprisingly, that there is very little difference in the duration curves for these variants, with a small difference occurring at the high net demand extreme only. There are two implications of this: firstly, we have some evidence that any conclusions drawn about the relationships between wind, hydro resource, and demand are robust to changes in the location and geographical spread of wind power projects compared to current plans. This also constitutes evidence that wind projects should be built where they are most likely to be profitable, in Kenya at least, with no motivation to compromise on this for a greater overall contribution to capacity adequacy. The curves are not included as figures for brevity, since the two model's results were so similar.

5.3 Temporal relationships between the wind and hydrological resources

This section presents analysis of the temporal relationship between the wind and hydrological resources, in statistical terms, to establish the extent to which the two are complementary. The more they are complementary, the greater the potential of wind capacity to contribute to capacity adequacy. Figure 4 presents 20-year series for modelled wind generation and Masinga reservoir inflow, using the *Original* scenario for wind capacity, the *Base* model variant for converting wind speed series into wind power, and the *Perfect Correlation* model for the reservoir inflow.

Figure 4 **Normalised 20-year series, monthly resolution, for the modelled wind resource (*Base* model, *Original* scenario), and the Masinga reservoir inflow (*Perfect Correlation* model)**



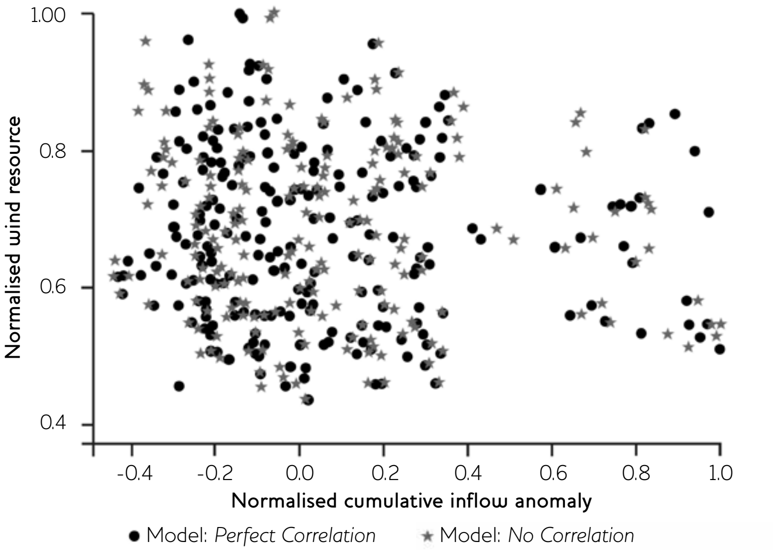
Source Authors' own.

The plot shows that the height of the wet season inflow peaks exhibit clear but complex clustering behaviour. The wind power series also displays long-term trends, over many years, but such behaviour is much smoother and less pronounced than for inflow. Indeed, the availability of the wind resource is consistently high, with even the worst month being >40 per cent of the best month. For the *No Correlation* model variant, the inflow series displays the same characteristics, but the exact location and amplitude of spikes within the clusters are occasionally quite different. The resources therefore appear to be somewhat complementary, although the relationship requires further elucidation – in particular, due to limited access to metered wind power output for calibration, results based on relative wind resource between months are expected to be more robust than the assessment of absolute level of wind resource.

Figure 5 provides an alternative view of the same datasets, making use of the cumulative inflow anomaly described in Section 4.4 which acts as a proxy for the Masinga reservoir level. In this case, the data are shown as a scatter plot, rather than as coincident time series. The cumulative anomalies naturally have a mean of zero, and were normalised to have a maximum of one for clarity of presentation. The wind power values are for the *Original* wind capacity scenario, and the *Base* wind model. Results are shown for both variants of the Masinga inflow model.

The figure shows that there is not a strong relationship between the two variables. During the most extreme anomaly values (roughly in the range -0.44 to -0.36), when wind generation might be most needed to help avoid generation shortfalls, the resource is disappointing (though

Figure 5 Relationship between wind resource (*Base* model, *Original* scenario) and cumulative Masinga inflow anomalies, for both inflow models



Source Authors' own.

there are few data points so confident conclusions cannot be made on this basis). However, most of the strongest months for the wind resource occur when the anomaly is either moderately or strongly negative, i.e. in the range -3.6 to -1, providing evidence that wind can make a useful contribution to adequacy. The two inflow models display good agreement for central values, but considerable disagreement at the extremes. The extent to which the wind resource is present when most needed appears somewhat more favourable when the Masinga inflow is modelled using the *No Correlation* variant. As the dataset is too small to draw firm conclusions, a more meteorological analysis, based on the long-term climatology of the region could greatly improve understanding of the relationship.

6 Conclusions

This article took as its premise the following idea: when evaluating the merits of potential investments in large-capacity VG projects, policymakers and stakeholders in the power systems of SSA countries (and elsewhere in the global South) would benefit from some insight into the impact the project might have on one of the biggest problems experienced by those systems. That problem is unreliable supply, and in some cases a constant suppression of demand, due to insufficient capacity adequacy. However, assessing the contribution of large VG projects to capacity adequacy in SSA countries is technically challenging, and has typically proved to be beyond the resources available to the system operators and regulators in studies to date. Both the need and the technical challenge are greatest in those countries where demand is growing rapidly, and that are likely to see a large penetration of variable renewable generation.

Despite the high technical barriers associated with thorough capacity adequacy assessment – perhaps chief among them being access to relevant data – this article has demonstrated that valuable insight can be gained from a relatively straightforward desktop analysis where limited data are available. In such a situation, the key uncertainties associated with the lack of data can be dealt with by developing several simple model variants, each using a different data source where possible.

The illustrative example of this approach presented in this article examined the wind resource in Kenya, with the objective of gaining insight into the potential for wind generation projects, with very large capacities in relation to the Kenyan power system, to contribute to capacity adequacy roughly within the next decade. Several variants were developed for the wind capacity scenarios and for the process of transforming wind speed time series into generated power. Assessing the wind resource with respect to capacity adequacy requires temporally matched time series for the system demand and the hydrological resource available – so several model variants were also developed for these series.

Results of the analysis indicate that there is a moderately complementary relationship between the wind resource and demand, and between the wind and hydro resources. The wind resource is also strikingly consistent, and seems able to significantly reduce many (but not all) of the highest demands likely to be experienced by the future system. This supports a view that the large wind projects that are either currently being built in Kenya, or will be in the near future, are likely to contribute significantly to generation adequacy of the system.

Notes

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1 University of Edinburgh.

2 University of Edinburgh.

3 Newcastle University.

4 Private conversation with Chair of Lowest Cost Power Development Plan Committee, Energy Regulatory Committee, Republic of Kenya, Nairobi, 10 June 2015; and private conversation with Chief Engineer for Generation Planning, Kenya Power, Nairobi, 9 June 2015.

5 Private conversation with Chair of Lowest Cost Power Development Plan Committee, Energy Regulatory Committee, Republic of Kenya, Nairobi, 10 June 2015; and private conversation with Chief Engineer for Generation Planning, Kenya Power, Nairobi, 9 June 2015.

6 Private conversation with Chair of Lowest Cost Power Development Plan Committee, Energy Regulatory Committee, Republic of Kenya, Nairobi, 10 June 2015.

7 Private conversation with Chair of Lowest Cost Power Development Plan Committee, Energy Regulatory Committee, Republic of Kenya, Nairobi, 10 June 2015.

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