The Future of Renewable Energy for Electricity Generation in sub-Saharan Africa

Paul A. Adedeji [1a], Stephen Akinlabi [b,c], Nkosinathi Madushele [a] and Obafemi Olatunji [a]

[a] Department of Mechanical Engineering Science, University of Johannesburg, South Africa.
[b] Department of Mechanical and Industrial Engineering, University of Johannesburg, South Africa
[c] Department of Mechanical Engineering, Covenant University, Ota, Nigeria.

Email: pauladedeji2k5@gmail.com

Abstract: Energy transition in the last decade has experienced increased quota of renewable energy in the global energy mix. In sub-Saharan Africa (SSA), the transition from the fossil fuel to the renewable energy source has been gradual. The state of renewable energy in the region in the next decade is the focus of this study. This study uses a single-layer perceptron artificial neural network (SLP-ANN) to backcast from 2015 to 2006 and forecast from 2016 to 2020 the percentage of renewable energy for electricity generation, exempting the hydropower in the energy mix of the SSA based on historical data. The backcast percentage renewable energy mix was evaluated using known statistical metrics for accuracy measures. The root mean square error (RMSE), mean absolute deviation (MAD) and mean absolute percentage error (MAPE) obtained were 0.29, 0.18, and 14.69 respectively. The result shows possibility of an increase in the percentage of renewable energy in the electricity sector in the region. In 2020, the percentage of renewable energy in sub-Saharan region is expected to rise to 4.13% with exclusion of the hydropower. With government policies encouraging the growth of the renewable energy as a means of power generation in the region, the predicted percentage and even more can be realized.

Keywords: Non-linear autoregressive ANN; Renewable energy; sub-Saharan Africa

1. Introduction

Renewable energy is fast becoming a global mantra aimed at mitigating climate change and global warming associated with the energy sector. The African continent is among the continents endowed with high potentials for renewable energy sources with their abundance being a geospatial variant. While the solar energy is ubiquitous, the biomass, and the hydropower are more abundant in the wet, southern, and central regions of the continent. Wind energy on the other hand has its large presence in east, north the southern regions of the continent [1]. It is alarming that about 56 % of the countries in Africa still

---

[1] pauladedeji2k5@gmail.com

experience periodic power outages and load shedding [1]. Quantitatively, about 2 % of her gross domestic products (GDP) is being lost to these [1]. The SSA is notable for high potential of renewable energy for power generation [2]–[6]. However, the SSA region is still referred to have the least energy access rate on the globe [7]. The renewable energy sources among other available energy sources in SSA have been identified to possess a very high prospect of transforming Africa's industrial sector with increased energy access either at mini-grid, micro-grid, or nano-grid levels, thus naturally creating competitiveness among small and medium-sized enterprises, and modular industries.

The sub-Saharan region constitutes a part of the African continent where about 80 % of the continent's population resides [8]. The region accounts for 13 % of the world population, but, provides only 4 % of its energy demand [1]. Despite the proliferation of the renewable energy sources as alternative and clean source of power generation, statistics showed that in 2010, about 95 % of people in the sub-Saharan region still depends on the solid biomass for cooking [9] and other unclean sources for power generation [10]. However, recent statistics show that about 600 million people in the region lack access to electricity and 890 million still depend on conventional types of fuels for cooking [11]. Even though, this statistic has reduced in compared to a decade ago, the percentage reduction is not laudable. The larger percentage of the present-day SSA still has significant reliance on fossil fuels for power generation with most being off-grid.

Electricity among other types of energy has remained one of the primary markers of socio-economic development [9], [12], [13]. Since 2012, over 100 million people per year have gained access to electricity across the globe as compared to the rate of 60 million people per year in the previous decade [14]. Globally, about 1.3 billion people lack access to electricity with almost half of this population residing in the SSA [3]. Since the eighties, the electrification rate of SSA has remained low with no increase in the power supply per capita [15], [16]. Clean energy revolution has, however, being identified as the tool for winning the present energy poverty fight in the SSA [17]. Even though access to affordable, reliable, sustainable, and clean energy for all forms the seventh Sustainable Development Goal (SDG), it has been established that this seventh SDG is the solution to the first goal- "*ending poverty in all its forms everywhere*" [18]. These encompasses energy in entirety, involving the electricity and clean fuel technologies for all use [19]. The United Nations in the development of 2030 agenda for sustainable development has the set time around the corner. It is expedient to evaluate where in the region is in meeting the seventh SDG and potential roadmaps towards achieving this with renewable energy sources.

Renewable energy integration into the energy mix of sub-Saharan African countries is gradually gathering steam with a yearly increase in the percentage it occupies within the energy strata. In the SSA, report shows that wind, solar and biomass resource is gradually increasing in their integration into the national grid of the several countries [1]. For example, South Africa, as one of the countries in SSA has one of the most developed renewable energy programme in the region [20]. The programme has attracted about 195 billion rands to South Africa, 25 % of which is from foreign investors [21]. Also, renewable energy, including hydropower accounts for about 80 % of the electricity generated in Kenya [22]. Kenya has the first geothermal spring in Africa. Other sources for power generation include hydropower, oil thermal, wind power, and cogeneration from sugarcane bagasse [22]. This makes her electricity generation system one of the most sustainable, globally. Strategic plans are being made by the country to meet the anticipated double increase in energy demand in 2020 and a six-times increase in 2030. Similarly, Ethiopia is endowed with abundance of renewable energy sources with a potential to generate over 60,000 megawatts from a nexus of wind, solar, hydropower, and geothermal. However, the country currently has 2,300 megawatts installed to serve her population of 95 million people, but with further plans to harness more of wind and geothermal resource in the country [23].

Empirical models are data driven models which unravel the hidden patterns and trends. They have been widely used in several studies with varying performance. Such models like Adaptive Neuro-Fuzzy Inference System (ANFIS), and artificial neural network (ANN) have found relevance in energy studies for short-term forecasting [24], [25] and long-term forecasting [26], [27]. These models learn patterns in data either using a supervised, unsupervised, semi-supervised, or deep learning approach [28]–[31]. These models can be autoregressive [32] or input/output [33]. The autoregressive models use the historical data at a specific delay to predict subsequent values within a trend. Many of these models fall into the category of self-organizing maps (SOMs). These SOMs models transforms the input of an arbitrary dimension into one or two-dimensional discrete map with neighbourhood constraint.

Energy is a subtle undertone of the industrial revolution with improved technologies for power generation prevalent in each revolution. It is saddening to realize that SSA countries were mere spectators in the first, second, and third industrial revolution. The fourth industrial revolution is closing-up on the sub-Saharan region at an alarming speed. To ensure that SSA countries are not spectators once again but key contributors, it is expedient to determine the percentage of renewable energy in the SSA energy mix in 2020 and a roadmap towards increasing this percentage as region prepares for the next decade. This study backcast and forecast the percentage of renewable energy sources exempting the hydropower in the energy mix of the SSA region using single layer perceptron non-linear autoregressive artificial neural network (NAR-ANN) with enhanced smoothing technique to achieve a percentage for 2020. The study also briefly discussed the roadmap to ensuring more of renewable energy is integrated into the energy mix in the SSA region.

2. Methodology

2.1. Data collection

Time series data of the percentage of renewable energy exempting the hydro resource was collected between 1971 and 2015 from the world bank database. The data forms a representation of the percentage of renewable energy nexus in the total energy mix of the 46 sub-Saharan African countries.

2.2. The Artificial Neural Network (ANN)

The ANN is a black-box modelling technique which imitates the biological nervous system in its mode of operation. The technique maps the input-output space by receiving inputs and processing them through a network of interconnected processing elements called neurons [34], [35]. Each neuron receives input signals with an associated weight from relative neurons or the input layer. A non-linear activation function which processes the signal in each neuron exist. ANN models are categorized by the number of layers as either a perceptron (with single layer) or a multi-layer perceptron (comprising multi-layers). They can also be categorized according to the input/output processing as either backpropagation, recurrent or gradient descent models. A typical perceptron consists of an input layer, a hidden layer, and an output layer. ANN has found its usefulness in intelligent non-linear function approximation, and time series forecast [36]. Basically, it has been commonly used as a forecasting technique due to its robustness and ability to learn different data patterns without a prior understanding of the system being modelled. Despite its several advantages, one of its setbacks is its black box nature. It does not explain explicitly its mode of operation unlike conventional models of data fitting.

2.3. Modelling technique

The non-linear autoregressive (NAR) neural network approach was used in this study for a short-term forecast of the percentage of renewable energy mix in the next decade. The NAR model is significantly useful in forecasting time series data from historical data. The autoregressive equation for a given series y_t can be represented by [32]:

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \cdots + a_n y_{t-n} + \varepsilon_t \tag{1}$$

where $a_1, a_2, \ldots a_p$ are called the autoregressive parameters and ε_t are normally distributed error term with a mean of zero and a finite variance σ^2.

From the least square method, the autoregressive model parameters were calculated using:

$$\varphi_0 = \bar{y}_0 - \sum_{i=1}^{p} \varphi_i \, \bar{y}_i, \tag{2}$$

$$(\varphi_1, \varphi_2, \ldots, \varphi_p)^T = \left(L_{\eta\eta}\right)_{p \times p}^{-1} \left(L_\eta\right)_{p \times 1} \tag{3}$$

where the observation mean, $\bar{y}_i, i = 0,1, \ldots, p$ can be calculated using:

$$\bar{y}_i = \frac{1}{n-p} \sum_{t=1+p}^{n} y_{t-p} \qquad i = 0,1, \ldots p \tag{4}$$

and the $L_{\eta\eta} = (S_{ij})_{p \times p}$ is a matrix in the pth order, however, $L_\eta = (S_1, S_2, \ldots, S_p)^T$ is a column vector in the pth order, whose constituting elements can be determined using:

$$S_{ij} = \sum_{t=p+1}^{n} (y_{t-i} - \bar{y}_i)(y_{t-j} - \bar{y}_j) \qquad i,j = 1,2, \ldots, p \tag{5}$$

$$S_i = \sum_{t=p+1}^{n} (y_t - \bar{y}_0)(y_{t-i} - \bar{y}_i) \qquad i = 1,2, \ldots, p \tag{6}$$

Estimating the coefficient of the autoregressive characteristic equation (3), $\hat{\varphi}_0, \hat{\varphi}_1, \hat{\varphi}_2, \ldots, \hat{\varphi}_p$, the autoregressive prediction model equation then becomes:

$$\hat{y}_{n+l|n} = \hat{\varphi}_0 + \sum_{i=1}^{p} \hat{\varphi}_i \, y_{n+l-i|n} \tag{7}$$

such that $\hat{y}_{n+l|n}$ is the $l-$step-ahead prediction at a time $n+l$.

The ANN modelling proceeds by a single-layer perceptron. A log-sigmoid transfer function was used for the hidden layer. The training process was performed with 1000 epochs as maximum possible iterations. Multiple trainings were performed towards minimizing the mean square error and avoiding underfitting and overfitting. Multiple trainings were experimented and the different number of neurons in the hidden layer tried with different training functions. A delay of 10 and a total number of neurons ($N_h = 30$) was used for the hidden layer; Levenberg-Marquart backpropagation algorithm gave the best results. A total of 31 iterations was reached before one of the stopping criteria (maximum gradient of

4.48×10^{-9}) was reached. It has been established in the literature that too many neurons in the hidden layer could cause overfitting or lack of generalization, thus resulting into large verification errors [37]. This was avoided in this study as much as possible. The script for the model was written on Matlab (2015a) and run on a computing device with a configuration of 4GB RAM, core i7 2.20GHz processor. A backcast and forecast for ten years were performed and the result compared with the observed values. Performance evaluation of the result using known metrics was carried out. Based on this, a decade forecast of the percentage of the renewable energy mix in the SSA was performed. Strategies towards achieving the increase in the renewable energy quota in the region was developed.

3. Results and Discussions

3.1. Historical renewable energy profile of the SSA

Shown in Figure 1 is a timeseries plot of the percentage of renewable energy integration for electricity generation in the SSA region for 45 years. This percentage includes all renewable sources except hydropower. It can be observed that the SSA region still has a low percentage of RE in sources for electricity generation. The data shows about three decades of RE for electricity generation in the region. The first decade in this data shows no significant change in the percentage. However, a significant increase is observed from four years after the first decade (from 1985). A decade from 1985 (up until 2005), there is a gradual increase in the percentage of RE in electricity generation. At 2005, the SSA achieved close to 1% renewable sources in electricity generation. However, a rapid increase in the use of renewable sources for electricity generation was observed in the third decade (from 2006 till 2015). This can be traced to a change in energy policy to accommodate more renewable energy sources in the energy mix at national levels. This was experienced in certain countries like South Africa, which inaugurated the Renewable Energy Independent Power Producer Procurement Programme (REI4P) in 2015 [38]. Similarly, renewable energy has been on the increase in other countries like Senegal, Ethiopia and so on with more plans to expand this at micro-grid level.
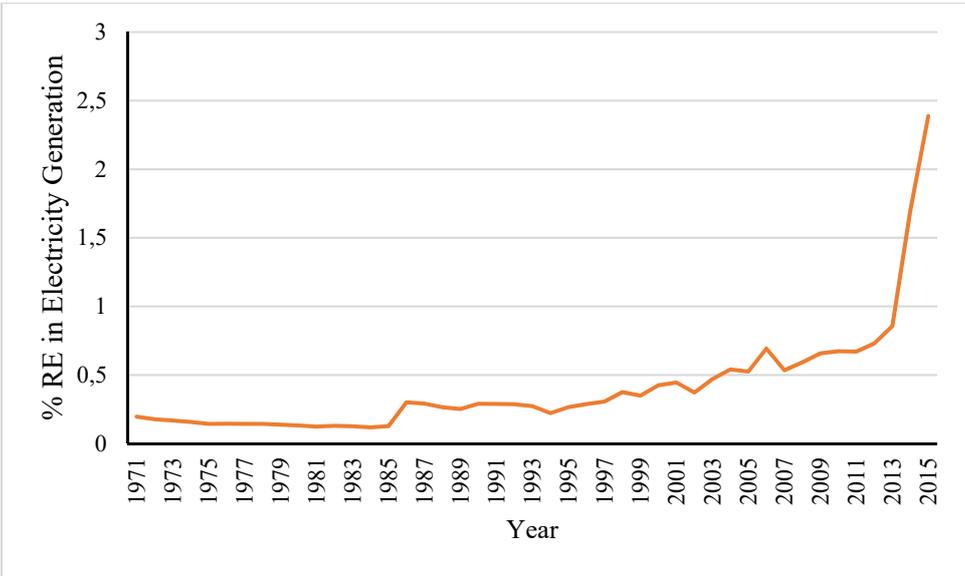
Figure 1. Percentage of Renewable energy in electricity generation for SSA between 1971 and 2015.

3.2. Model results

From the range of the data (2015), a backcast of 10 years and a forecast of 5 years was performed. The backcast was compared with the actual renewable energy percentage (without the hydropower) as shown in Figure 3. A 5-year ahead forecast was performed between 2016 to 2020. The result shows a gradual increase in the percentage of renewable energy to be expected in the energy mix of SSA region. Shown in Figure 3 is result of the ANN forecast compared to the observed values. Common statistical performance measures were used to compared the actual and predicted value for the 10 years data, like root mean square (RMSE), mean absolute deviation (MAD), and mean absolute percentage error (MAPE) and calculated as using equations (1) to (3). The result is as presented in Table 1.
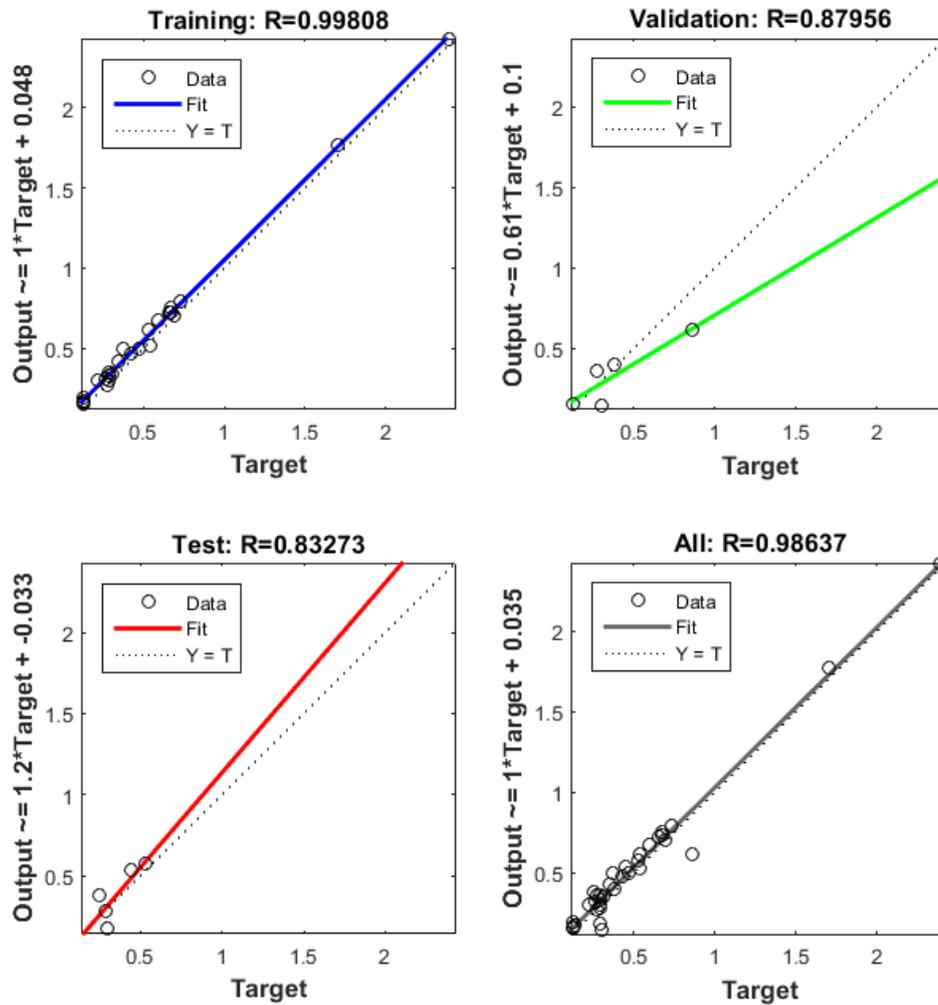
Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{1=1}^{N}[y_i - \widehat{y_i}]^2}{N}} \qquad (8)$$

Mean Absolute Deviation (MAD)

$$MAD = \frac{1}{N}\sum_{i=1}^{N}|y_i - \mu| \qquad (9)$$

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \widehat{y_i}}{y_i}\right| \times 100\% \qquad (10)$$

Figure 2. Regression plot for the SLP-ANN model (this comprises of the training, testing, validation, and model overall regression)

Table 1. Comparison results between actual and predicted percentage renewable energy.

| Performance Metric	
RMSE	0.28993
MAD	0.18186
MAPE	14.61928

The regression value at model training, testing and validation obtained were 0.99808, 0.83273, and 0.87956 respectively. This values as close to unity signifies that the model proceeds effectively in training, testing, and validation. The overall regression for the model being 0.98637 also shows the accuracy of the model.
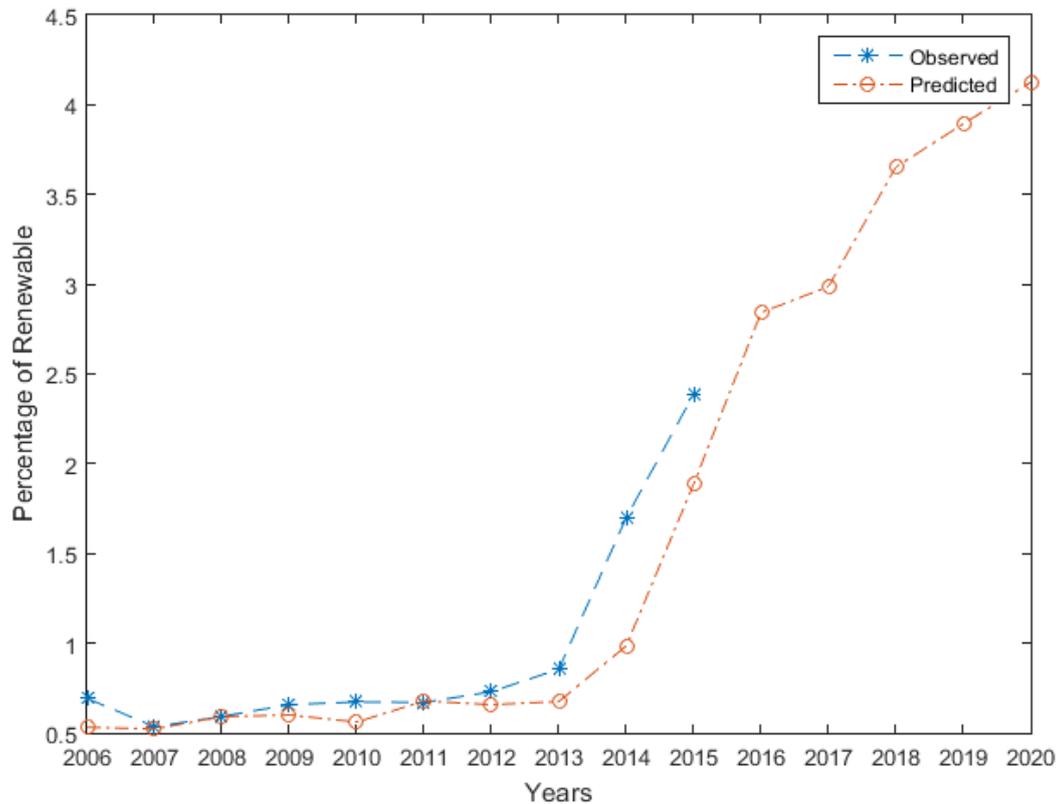
Figure 3. A forecast of percentage renewable energy between 2006 and 2020 in the SSA.

The error deviation from the mean was observed to be less than 0.5 and the MAPE value shows that the forecast is off by 14.62%. This shows reliability of the 5-year forecast. Presently, to the best of the authors knowledge, there have been no documentation on the percentage of renewable energy exempting the hydropower in the sub-Saharan region for 2020 (the last period in Figure 3) which necessitated this study. However, the result of this study was related to the REmap 2030 Africa analysis, a country-based analysis, which investigated the demand profile, resource endowment, and the potential for harvesting accounted for. The analysis showed that the African continent has explored less than 50% of her renewable energy potentials. The REmap 2030 analysis identified hydropower as occupying 14% of the African total electricity supply in 2013 (Figure 4) and it has been the predominant source of generation in the eastern and central regions [1]. However, other sources like photovoltaic (PV), concentrated solar power (CSP), and wind were envisaged to increase significantly within the African energy mix by 2030. They are envisaged to occupy close to half of the electricity generation with 20% for hydropower. Modern renewables are envisaged to share close to 22% of the African energy mix in 2030.

North Africa is envisaged to lead the trail in 2030 as show in Figure 4. The SSA region comprises largely of other African regions exempting the Northern Africa. Small hydro is expected to dominate the mix of the SSA in 2030, which is exempted in this study. Other renewable energy sources occupy a small quota except the solar PV in the Southern Africa region. However, a backcast from 2030 to the 2020, the focus of this study, we can say that the percentage of renewable energy sources exempting the hydropower in 2020 will be close to the predicted in this study. A marginal variation can exist which may not be statistically significant from the result obtained in this study.
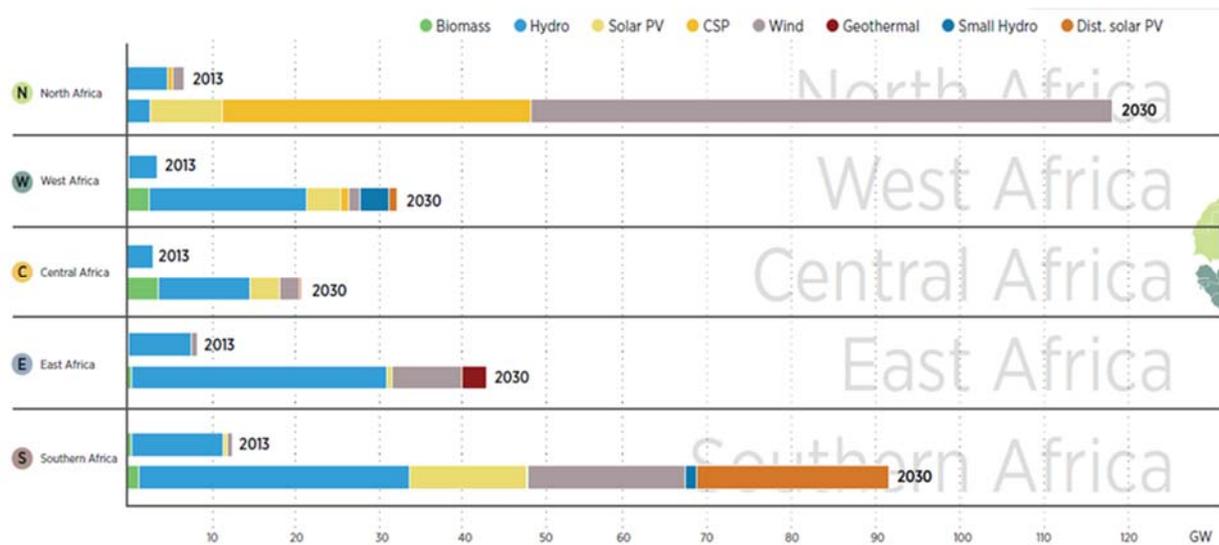
Figure 4. Renewable energy prospect of Africa in 2030. Source [1]

3.3. Achieving Increase in Renewable energy in SSA.

Renewable energy is highly profiled on a global scale. This is not only due to its low-carbon nature but also due to its abundance compared to the non-renewable sources. Increasing its quota in the energy mix of the SSA largely depends on government policies and reforms. It has been established that the region has a high resource availability index [1]. The sustainability of renewable energy largely depends on diversification of sources in the region. Almost 87% of the world population are living without electricity access, the rural areas of SSA and part of Asia significantly contribute to this value [19]. The encouragement of renewable energy micro-grids will significantly reduce this deficit, most especially in SSA where resource availability is not a problem. The industrial sector constitutes one of the largest energy consuming sectors in the SSA. Energy efficiency in this sector through the adoption of modern facilities will reduce energy consumption rate, which in turn reduce pressure on energy generated. From the 2018 World Bank report, there was observed for the first time a fall in the percentage of people without energy access with Eastern Africa being the driving region [19]. This percentage can be further reduced by encouraging modular off-grid systems which rests on effective strategic planning at national level.

4. Conclusions

This study was able to forecast the percentage of RE in the energy mix of the sub-Saharan region from 2016 till 2026. This study does not take into consideration the socio-technical aspect of RE and the dynamics of the renewable energy system, like change in policy, political instability, environmental conflicts in the RE space relative to existing policies, which could result in the closure of production plants. Historical data was only used for the intelligent forecast. It can be established from the result that RE percentage in the energy mix of the SSA will increase in the next decade. The actual percentage of RE in the energy nexus could be more, or less than the forecast in this study. This largely depends on the existing government policies, socio-economic factors, efficient siting of RE facilities for electricity generation, environmental concerns (especially in wind energy harvesting) and many other factors.

5. Recommendation

Further studies with the use of systems dynamics, which integrates several obvious and latent variables in the renewable energy system is recommended. This will give a holistic view of the renewable energy integration in the electricity generation.

Acknowledgements

References

[1]   IRENA, "Africa 2030: Roadmap for a renewable energy future," Abu Dhabi, 2015.

[2]   A. Aly, S. S. Jensen, and A. B. Pedersen, "Solar power potential of Tanzania: Identifying CSP and PV hot spots through a GIS multicriteria decision making analysis," *Renew. Energy*, vol. 113, pp. 159–175, 2017.

[3]   P. Rolffs, D. Ockwell, and R. Byrne, "Beyond technology and finance: pay-as-you-go sustainable energy access and theories of social change," *Environ. Plan. A*, vol. 47, no. 12, pp. 2609–2627, 2015.

[4]   P. P. Silva, P. A. Cerqueira, and W. Ogbe, "Determinants of Renewable Energy Growth in Sub-Saharan Africa :," *Energy*, vol. 156, 2018.

[5]   S. Batchelor, E. Brown, J. Leary, N. Scott, A. Alsop, and M. Leach, "Solar electric cooking in Africa: Where will the transition happen first?," *Energy Res. Soc. Sci.*, vol. 40, no. January, pp. 257–272, 2018.

[6]   C. G. Monyei, A. O. Adewumi, and K. E. H. Jenkins, "Energy (in)justice in off-grid rural electrification policy: South Africa in focus," *Energy Res. Soc. Sci.*, vol. 44, no. May, pp. 152–171, 2018.

[7]   J. Corfee-Morlot, P. Parks, J. Ogunleye, and F. Ayeni, "Achieving Clean Energy Access in Sub-Saharan Africa," 2019.

[8]   S. Karekezi and W. Kithyoma, "Renewable energy in Africa: Pospects and Limits," 2003.

[9]   A. Brew-Hammond, "Energy access in Africa: Challenges ahead," *Energy Policy*, vol. 38, no. 5, pp. 2291–2301, 2010.

[10] I. Dunmade, N. Madushele, P. A. Adedeji, and E. T. Akinlabi, "A streamlined life cycle assessment of a coal-fired power plant: the South African case study," *Environ. Sci. Pollut. Res.*, 2019.

[11] IEA, "World Energy Outlook 2018," Paris, 2018.

[12] B. Pillot, M. Muselli, P. Poggi, and J. B. Dias, "Historical trends in global energy policy and renewable power system issues in Sub-Saharan Africa: The case of solar PV," *Energy Policy*, vol. 127, no. December 2018, pp. 113–124, 2019.

[13] A. G. Dagnachew, P. L. Lucas, A. F. Hof, D. E. Gernaat, H. S. de Boer, and D. P. van Vuuren, "The role of decentralized systems in providing universal electricity access in Sub-Saharan Africa – a model-based approach," *Energy*, vol. 139, pp. 184–195, 2017.

[14] IEA, "World Energy Outlook 2017," 2017.

[15] J. Klugman, "Human Development Report 2011 – Sustainability and Equity: A Better Future for All," 2011.

[16] F. Birol, "World Energy Outlook 2016," 2016.

[17] J. Corfee-Morlot, P. Parks, J. Ogunleye, and F. Ayeni, *Achieving clean energy access in sub-Saharan Africa A case study for the OECD, UN Environment, World Bank project: "Financing.* 2018.

[18]   R. V. Nalule, *Energy Poverty and Access Challenges in Sub-Saharan Africa: The role of regionalism*. Palgrave Macmillan, 2019.

[19]   The World Bank, "Tracking SDG7: The Energy Progress Report 2018," 2018.

[20]   D. Richard and A. Colin, "Renewable energy gathers steam in South Africa," *Renew. Sustain. Energy Rev.*, vol. 41, pp. 390–401, 2015.

[21]   S. Louise, M. Khodani, K. Karin, M. Mbali, and F. Stephen, "Renewable Energy : Facts and Futures The energy future we want," 2017.

[22]   J. K. Kiplagat, R. Z. Wang, and T. X. Li, "Renewable energy in Kenya : Resource potential and status of exploitation," *Renew. Sustain. Energy Rev.*, vol. 15, pp. 2960–2973, 2011.

[23]   G. Lin and W. Butterfield, "Power Africa in Ethiopia," 2016.

[24]   A. Buga *et al.*, "Short-term forecast of generation of electric energy in photovoltaic systems," vol. 81, no. November 2016, pp. 306–312, 2018.

[25]   F. Ziel and R. Weron, "Day-ahead electricity price forecasting with high-dimensional structures: Univariate vs. multivariate modeling frameworks," *Energy Econ.*, vol. 70, pp. 396–420, 2018.

[26]   B. Akdemir and N. Çetinkaya, "Long-term load forecasting based on adaptive neural fuzzy inference system using real energy data," *Energy Procedia*, vol. 14, pp. 794–799, 2012.

[27]   X. Yuan, Q. Tan, X. Lei, Y. Yuan, and X. Wu, "Wind power prediction using hybrid autoregressive fractionally integrated moving average and least square support vector machine," *Energy*, vol. 129, pp. 122–137, 2017.

[28]   K. P. Amber, R. Ahmad, M. W. Aslam, A. Kousar, M. Usman, and M. S. Khan, "Intelligent techniques for forecasting electricity consumption of buildings," *Energy*, vol. 157, pp. 886–893, 2018.

[29]   K. Lee, D. Booth, and P. Alam, "A comparison of supervised and unsupervised neural networks in predicting bankruptcy of Korean firms," *Expert Syst. Appl.*, vol. 29, no. 1, pp. 1–16, 2005.

[30]   S. Silva, L. Vanneschi, A. I. R. Cabral, and M. J. Vasconcelos, "A semi-supervised Genetic Programming method for dealing with noisy labels and hidden overfitting," *Swarm Evol. Comput.*, vol. 39, no. September, pp. 323–338, 2018.

[31]   M. A. Waris, A. Iosifidis, and M. Gabbouj, "CNN-based edge filtering for object proposals," *Neurocomputing*, vol. 266, pp. 631–640, 2017.

[32]   P. A. Adedeji, S. Akinlabi, O. Ajayi, and N. Madushele, "Non-linear autoregressive neural network (NARNET) with SSA filtering for a university enegy consumption forecast," in *16th Global Conference on Sustainable Manufacturing- Sustainable Manufacturing for Global Circular Economy*, 2019, pp. 176–183.

[33]   P. Adedeji, N. Madushele, and S. Akinlabi, "Adaptive Neuro-fuzzy Inference System (ANFIS) for a multi-campus institution energy consumption forecast in South Africa," in *Proceedings of the International Conference on Industrial Engineering and Operations Management Washington DC, USA, September 27-29, 2018*, 2018.

[34]   H. K. Ghritlahre and R. K. Prasad, "Application of ANN technique to predict the performance of solar collector systems - A review," *Renew. Sustain. Energy Rev.*, vol. 84, no. December 2017, pp. 75–88, 2018.

[35]   T. A. Tutunji, "Parametric system identification using neural networks," *Appl. Soft Comput. J.*, vol. 47, pp. 251–261, 2016.

[36]   A. Khashei-Siuki and M. Sarbazi, "Evaluation of ANFIS, ANN, and geostatistical models to spatial distribution of groundwater quality (case study: Mashhad plain in Iran)," *Arab. J. Geosci.*, vol. 8, no. 2, pp. 903–912, 2015.

[37]   S. A. Kalogirou, "Artificial neural networks in energy," *Int. J. Low Carbon Technol.*, no. March, pp. 201–216, 2015.

[38]   Ministry of Lands Mines and Energy, "Renewable Energy and Energy Efficiency Policy and Action Plan," 2016.