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Analysis of solar energy potentials of five selected south-east cities in nigeria using deep learning algorithms

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Abstract

This study presents a meticulous examination of the solar energy potential of five selected metropolitan cities (Abakaliki, Awka, Enugu, Owerri, and Umuahia) in Eastern part of Nigeria using deep learning algorithm, specifically the Long Short-Term Memory (LSTM) model. These cities, despite being characterized by extended rainy seasons and a high level of cloudiness, are suitable environment for solar power generation and investment opportunities. The employed methodology capitalized on the LSTM deep learning approach to analyze and predict energy generation, utilizing comprehensive hourly weather data from the National Airspace Agency (NASA). The data set comprised various parameters, such as date/time, solar azimuth angle, temperature, humidity, wind speed, wind direction, cloud cover, and power, enabling a thorough analysis of each city. To ensure accuracy, energy prediction capabilities were benchmarked against real-time datasets from a solar power plant in Ulsan, South Korea, thereby training and fine-tuning the model for precision. The LSTM model's performance metrics were maintained at a learning rate of 0.07, a batch size of 150, and a train-test split ratio of 0.8 to 0.2. Data validation exhibited a mean square error (MSE) of 0.01, demonstrating the model's reliability. Results showed Enugu as having the highest solar energy potential, averaging 6.25 kWh/day, while Awka registered the most substantial electricity demand across various sectors. These findings highlight the substantial potential for photovoltaic (PV) power systems and advocate for the immediate implementation of renewable energy policy in the selected cities. These are expected to bring about significant implications for future renewable energy environmentally friendly investments in Nigeria and globally.

Keywords Nigeria, Energy crisis, Power generation, Renewable energy, Solar energy potential, Deep learning procedures, Energy policy, Private sector participation, National energy security

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Introduction

Background

Nigeria is endowed with abundant natural resources and diverse energy potentials including fossil fuels and renewables. Despite these abundant resources, the country is burdened by persistent energy crises that have hampered socio-economic growth over the past three decades. The current energy infrastructure is inadequate to meet the needs of its growing population of over 200 million, evidenced by inadequate power generation and recurrent power outages. Specifically, Nigeria's installed capacity of 15,000 MW significantly underperforms relative to its actual generation, which oscillates between 3500 and 5000 MW. This capacity is alarmingly inferior when compared with nations like South Africa, which sustains a population of 59 million with an installed generating capacity of 54,000 MW as at the year 2022 (Pierce & Roux, M.l., 2023). This power deficiency in Nigeria pushes industries and consumers towards self-generation, a costly alternative.

Energy is very vital for environmental sustainability. Its importance transcends all aspects of society's socio-economic and cultural development. The energy industry is inextricably linked to Nigeria's economy. Apart from the macroeconomic benefit of energy, it does also have significant importance in poverty alleviation, facilitates productivity and general well-being of the citizenry. The energy industry and other sectors are intertwined in many ways. The energy sector makes a significant contribution towards the growth and development of the nation's economy. This is because uninterrupted energy supply is needed to drive and boost a nation's economy. The ambition to ensure and provide uninterrupted, modern, increased energy supplies to meet the growing demands of energy requires humungous sum of financial and human resources. This is evidently true owing to the huge amount of money needed for investment in the energy sector (AfDB, 2019; IRENA & CPI, 2023). To enable all the countries in Africa to achieve uninterrupted access to energy, the African Development Bank estimated that an annual investment of about 29–39 billion USD is required till the year 2025 (AfDB, 2019). The bank also pointed out that more investment will be required when investment in low-carbon technologies is given higher priorities. The energy demand within the West-Africa sub-region, it is estimated to grow by about 8.9%, of which one-quarter of the demand will be driven by Nigeria (AfDB, 2019) by 2030. In view of this, the Nigerian government has decided to embark on developing a comprehensive energy masterplan to bring to fore and to implement the provisions of the National Energy Policy to achieve the aims and objectives of the national power project. The national energy masterplan makes information available for potential investors and facilitates an all-round development in the industry. Without a well-designed plan that gives high premium to major improvement in energy services, the actualization of the government's transformation agenda and sustainable energy for all by 2030 wouldn't be possible (Shulla et al. 2030). The masterplan also describes who to carry out what activities amongst the stakeholders in the energy sector. Nigeria as a nation, is blessed with abundant varieties of renewable energy sources, the reserves are shown in the Table 1.

It is on record that Nigeria is the 7th largest reservoir of crude oil and the 9th country with the largest deposit of natural gas in the world. The ratio of the associated and non-associated natural gas is 54:46. Efforts are being made by the government to harness the tar sands and coal deposits in the country by providing an enabling environment to further encourage private investors-driven sand and tar sub-sectors. The major provision of the Nigerian energy policy is in the area of utilization of the country's abundant energy resources for sustainability, growth, and overall development. The energy masterplan enunciates the sets of activities through which that can be achieved. In recent times, renewable energy has been drawing so much attention by all and sundry. It is clean, safe, and not limited in resources (Abolarin et al. 2022). Renewable energy is an ideal source of energy for both domestic and commercial activities. Despite its intermittency, the renewable energy remains the cleanest source of energy

Table 1 Nigeria's Energy Reserve as of January, 2023 (ECN, 2022)

S/N	Resource		Reserves	References
1	Oil		37.1 B barrels	EIA
2	Gas		208.6 TCF	ECN
3	Coal and Lignite		2.73 B Metric tons	ECN
4	Tar Sands		31 B barrels of oil equivalent	ECN
5	Large Hydro		14.1 GW	ECN
6	Small Hydro (≤ 30 MW)		5.2 GW	ECN
7	Solar radiation		3.6 – 7.1 kWh/m^2/day	EIA
8	Wind		(2 – 5) m/s @ a height of 10 m	ECN
9	Biomass	Wood	9.04 M ha of forest & woodland	ECN
		Municipal waste	32 M tons/year	ECN
		Animal waste	245.1 M assorted animals	ECN
		Energy crops and Agro residue	70.8 M ha of agricultural land	ECN
10	Nuclear Element		Not yet quantified	ECN

not just for home use, but also for industrial use. Indeed, renewable energy potentials vary significantly depending on the conditions and the characteristics of the place where they are located, which makes it difficult to estimate how much benefit in terms of power is going to be obtained from them. Two of the most relevant energy sources in recent years have been solar and wind. Hence, they are the energy sources that can be harnessed across different regions, countries, and even continents. Owing to the fact that climate change and its attendant effects have been gaining much attention from governments across the globe, renewable energies such as solar and wind are now becoming increasingly considered as the most viable alternatives to fossil fuels.. There are two kinds of solar energy; namely, thermal solar energy which converts solar radiation into thermal energy and photovoltaic solar energy (Abolarin et al. 2022). The photovoltaic solar energy converts solar radiation into electricity that can be used for other benefits other than just heating. Despite its wide areas of usage, solar photovoltaic energy has varying performance from panel to panel, and from region to region, depending on the climatic condition in those regions, as well as the weather condition per time (see Fig. 1 for detail) (Laguarda et al. 2023). The COP26 summit held in Glasgow, Scotland envisions the possibility for a universally acceptable clean energy source for sustainable development. One of the key challenges to achieving this vision lies on the low reliability of certain renewable energy sources.

The energy demand and supply imbalance in Nigeria is so much, as there is low energy access throughout the country. The situation of load shedding and cuts in the supply of electricity is a reoccurring event across the Nigerian states, especially in the semi-urban and rural areas. To ensure that there is an increased access to electricity supplies, there is a need to emphasize that the energy producers and consumers should inculcate energy management culture and best practices (Abolarin et al. 2011, 2013, 2014, 2015). Every energy consumer has got a role to play in the improvement of energy efficiency and conservation. Therefore, there is a need for energy conservation of the available supply by all sectors of the economy so as to achieve energy performance improvement. Energy efficiency still is faced with a lot of challenges such lack of awareness, lack of baseline energy consumption data, performance improvement implementation of measurement and verification of energy consumption data, inadequate manpower development, non-implementation of energy laws and regulations and improper billing (example, estimated metering system) by utility companies and corrupt practices by power distribution companies (Adoghe et al. 2023; Dahunsi et al. 2021; Oseni, 2015).

The long short-term memory (LSTM) is the deep learning approach that was used for data analysis and solar power prediction in this study. Deep learning has recently gained a lot of popularity in doing scientific analysis; its algorithms are being utilized by both the academia and industry in solving complex problems. Deep learning uses ANNs to perform complex computations and analysis on large volume of data. It is a type of machine learning that works as a replica of human brain.

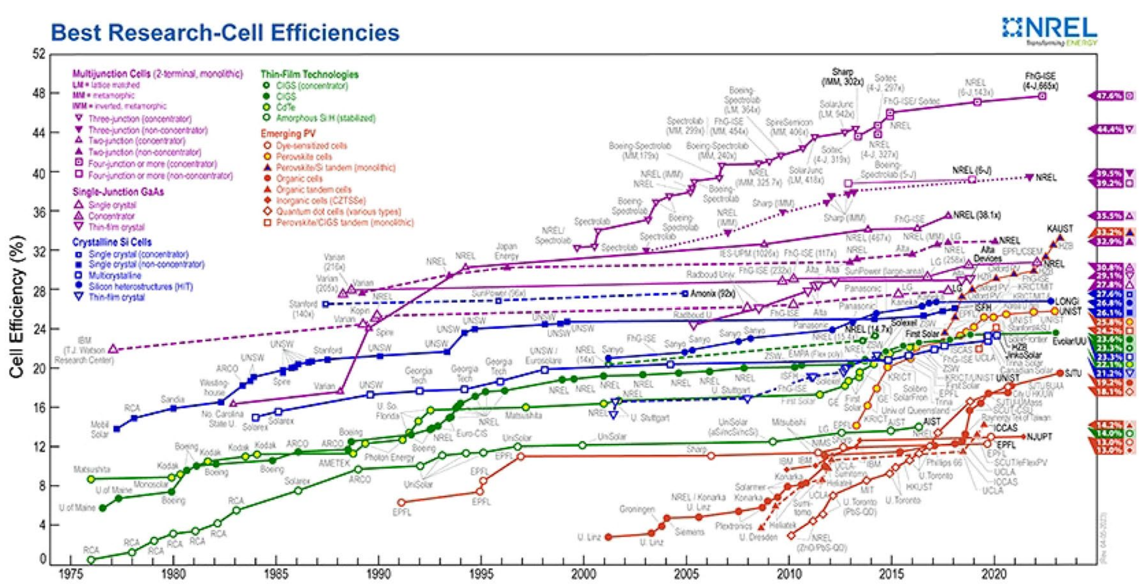


Fig. 1 Range of PV conversion efficiencies of solar panels from 1976 to 2020 NREL

It trains machines by learning from past examples. The LSTM model is a very good model for the prediction of renewable energy. The model has been discovered to be one of the best deep learning models available for accurate prediction of energy and is best suited for time-series analysis. LSTMs can learn and memorize long-term dependencies, it can recall past information for a long period. Apart from time-series predictions, LSTM can also be used for speech recognition, music composition, etc. In training the model, Keras library was used to facilitate fast experimentation and prototyping. It is a high-level neural network for building and training deep learning models. Keras can run on several platforms such as tensorflow, theano, and so on.

Statement of problem

The supply of energy in Nigeria is very epileptic. Also, there are still large unreached areas without electricity, especially in the interior villages. In a study conducted by the Presidential Advisory Committee (PAC) on 25-year Power Development Plan, the projected electricity demand for a 10 percent yearly GDP growth was put at about 16000 MW, 30000 MW and 192000 MW for the years 2010, 2015 and 2030, respectively (Mansur, 2020). The accomplishment of the above projected generation capacity will ensure that the per capita electricity consumption would be almost 5026 kWh. This means that it will be at par with the present consumption level in many yet-to-be industrialized nations. The study also reveals an electricity generation mix of Nuclear at 2%, Hydro 7%, Renewable energies 10%, Coal at 11%, and Natural Gas was put at 70% in the long-term. As at the moment, Nigeria's energy consumption is below the average of the consumptions in most industrializing countries.

As at now, the infrastructural capacity of the Nigerian electricity value chain is inadequate to meet the country's energy demand. Even the available facilities are mostly outdated. Nigeria's electricity generation capacity is put at about 15 GW, while the actual power generation revolves around 3500 and 5000 MW for a country of over 200 million people. This low generation capacity has caused an increased number in power cuts and load shedding. It has also affected the economy tremendously in all facets, including industry, manufacturing, transportation, construction and general services. Furthermore, there has not been any significant investment in energy sector since 1999 to date, and most of the generating plants owned by the government are not operating at the supposed capacity. For example, the Egbin power plant which has an installed capacity of 1300 MW but is operating at about 600–700 MW capacity. The Nigeria's national grid has a high rate of power losses in terms of transmission and distribution. The losses are reported to be higher than internationally acceptable standard. A few other power projects such as the Mambilla hydro power plant project have been in the pipeline for decades, yet, they have not been completed. The Mambilla power plant is expected to generate more than 3 GW of electricity. To achieve the government's projected high economic growth scenario in relation to the forecasted electricity demand base value of 322,452 MW in 2030, there is a need to integrate renewable energy (such as solar PV) to the national grid.

The major hiccups to the accelerated development of technology to exploit, explore, and harness renewable energy in Nigeria are unstimulated demand, non-implementation of the available regulatory and institutional framework, as well as lack of incentives for private investors (Oyedepo, 2012). Nigeria's annual consumption of electricity has been steadily growing. Making it even increasingly important to urgently expand energy supply through a robust investment planning. Energy consumption has increased from 1273 GWh in 1970 to 29,573 GWh in 2019. This, however, represents a repressed demand caused by inaccessibility to the national grid and insufficiencies of the electricity supply.

Another major problem of energy production, distribution and consumption in the country is related to environment and climate change; mainly deforestation and pollution (air, water and soil). Oil spillage, pipeline bunkering and vandalism, as well as gas flaring have taken a toll on the nation's economy over the past decades (Mansur, 2020). Owing to the above-mentioned ill-practices which have far reaching negative consequences, there is need to consider and infuse environmental impact into Nigeria's energy utilization strategy.

Objective of the study

To find solution to the problem, or at least ameliorate the effect of power failure in the country, this study seeks to analyze the solar energy potentials in the five (5) states that make-up the southeastern part of the country. This study concentrated on the analysis of solar energy potentials and ascertains the reliability of daily power output prediction with deep learning algorithm in the five selected cities in the eastern part of Nigeria. After conducting the studies, relevant recommendations are made to the authorities as well as private investors on the need to invest in solar energy as one of the most viable options to solving the erratic power supply issues in Nigeria.

Scope/delimitation

The five targeted cities are Abakaliki city in Ebonyi state, Awka in Anambra state, Enugu in Enugu state, Owerri municipal in Imo state, and Umuahia in Abia state. These cities also double as the state capitals, are representative samples of the remaining cities in the target area. The cities have similar weather and climatic condition with other cities within the respective states/regions. This invariably means that the result and recommendations from this study are limited to the states within the country or other regions with similar weather data.

Contribution to knowledge

The scientific approach like the one in this study can help establish guide and requirement for the determining solar power potential in Nigeria. This will contribute meaningfully in solving the decade long power failure problem in Nigeria by analyzing the solar potentials of various states/regions and making appropriate recommendation on how to utilize the available solar potential in solving Nigeria's perennial electricity blackout across the country. This will also pave the way for solar PV to be part of Nigeria's energy mix, in line with the country's energy masterplan of 2022.

Current status of policy

Nigerian energy policy

Developing and utilizing energy is dynamic. It involves constant update and review within a reasonable timeframe. The inherent climate action benefits of renewable energy sources have brought unprecedented changes on energy policies across the globe, helping in reshaping the clean energy plans, design, investment landscape, and deregulation in the energy industry (Ang et al. 2022). Similarly, energy policy is now serving as a driving force for foreign direct investments across many economies of the world. A crucial benefit of energy policy is the eventual application of energy resources to environmental sustainability, economic growth and development of many nations. Consequently, the Nigerian energy policy (ECN & National energy policy., 2022) is divided into different sections of energy resources and further grouped into short, medium and long-terms scenarios for easy implementation of the policy. Some of the main objectives of Nigeria's energy policy include but not limited to:

- Ensure the procurement of a nation-wide energy resources, including numerous energy sources option so as to be able to achieve energy security and efficiency.
- Improve the provision of electricity, thereby improving revenue for the government as well as for private business.
- Provision of clean, affordable, sustainable, and environmentally friendly energy resources for national development.
- Ensure energy efficiency for optimum energy utilization and consumptions.
- Encourage private sector investment into the energy sector through regular engagement with investors on ways to improve energy access.
- Engender bilateral and multilateral cooperation on energy investments across Africa, Europe, Asia, and the Americas.

Nigeria has a huge deposit of renewable energy resources such as wind, solar, hydrogen, hydro, animal wastes, etc. (Akinbami et al. 2021; Eweka et al. 2022). The nation's population has been projected to be on the rise, while energy demand is also expected to rise exponentially (Dioha & Emodi, 2030; Ibrahim et al. 2021; Pelz et al. 2023). Hence, the conventional energy sources such as coal, oil and gas would to be re-evaluated in the mix needed to meet the growing demand of electricity and achieve energy prosperity and sustainability in the country. To achieve the needed sustainability, the country is making concerted efforts to increase percentage of renewable energy in the nation's energy mix in accordance with the Sustainable Development Goal (SDG-7), and to also combat the negative effects of climate change in line with the Climate Action (SDG-13). Moreover, a working energy policy stands a chance to boost investment in renewable energy and create jobs for the citizenry, thus improving their living standards. Hence, Nigeria needs to urgently work on expanding the utilization of renewable energy to facilitate environmental sustainability and economic development (Failed, 2012a). The objectives of Nigeria's renewable energy policy can be summarized as itemized below:

- To exploit, harness, and explore renewable energy resources and effectively integrate them with gas, nuclear, and other energy sources for a balanced energy mix in the country.
- To consider renewable energy resources in national energy planning, so as to achieve the necessary expertise and technical know-how for the development of an efficient, reliable, and affordable energy for the development of the country.
- To formulate and implement policies that would ensure the provision of reasonable electricity pricing system that will be acceptable to both the consumers and the suppliers of electricity.
- The establishment of energy policies according to international best practices for the development and utilization of renewable energy.
- To encourage the use of renewable energy, and possibly provide incentives to farmers to use renewable energy for agricultural activities.

Table 2 Summary of renewable energy targets in GW (7%, 10% and 13% GDP growth rate) (ECN, 2022)

S/N	Renewable energy system	GDP growth rate								
		Short term			Medium term			Long term		
		7%	10%	13%	7%	10%	13%	7%	10%	13%
1	Large hydropower (LHP)	3	4	11.21	6	8	12.13	6	8	12.13
2	Small hydropower (SHP)	0.043	0.350	0.32	0.533	1.332	0.76	0.533	1.332	2.6
3	Solar PV	1.4	2	2.5	3	4	5	20	25	30
4	Solar Thermal	-	-	-	0.045	0.936	1.40	6	12	18.13
5	Biomass	0.005	0.005	0.005	0.016	0.023	0.03	0.050	0.077	0.1
6	Wind	0.020	0.028	0.036	0.022	0.032	0.04	0.030	0.042	0.05
	All Renewable (GW)	4.468	6.383	14.07	10.026	14.323	19.36	32.613	46.451	63.02
	All Energy Resources (GW)	26	32	48	52	72	90	160	230	315
	% RE	17%	20%	29%	19%	20%	22%	20%	20%	20%

- To support and possible provide finances for the development of technologies for the efficient utilization of renewable for economic development.

Environmental experts have been calling on world leaders to take urgent actions to avert the imminent dangers associated with of over-dependence on fossil fuels, such as oil, gas, and coal in driving economic activities (Dwivedi et al. 2022; Ekins & Zenghelis, 2021; Santos et al. 2022). Global warming which used to be a speculative science has now appeared real to all and sundry, making it even more critical in addressing the imminent danger of climate change (Abbass et al. 2022). Rising sea levels, flooding, desertification, draught have become a perennial problems across the globe (Klingelhöfer et al. 2020). There is now a global consensus for alternative energy sources to drive the future industrialization and economic development (Babayomi et al. 2022; Zhang et al. 2022); and renewable energy resources and technologies are the most favored for future economic development.

Some of the major constraints inhibiting the efficient development of the technologies required for the exploration and exploitation of renewable energy in Nigeria are lack of the implementation and enforcement of relevant policies and regulatory frameworks that would encourage private sector investment in the industry. The comparatively low quality of the systems and the high preliminary cost of investment also constitute as barriers to the growth of the energy market. Consequently, if Nigeria is to project the huge potentials of the renewable energy resources that are available on its territory, those barriers should be totally taken off, through substantial investment in terms of building critical infrastructures for renewable energy development and utilization. There is also a need for investment in areas of research and development, capacity development and the strengthening of the on-going economic reforms to create an environment that is investor friendly.

Going by a 7% GDP growth rate, and the Energy Commission of Nigeria's projected electricity supply template of about 26 GW, 52 GW and 160 GW in the short, medium and long-terms scenarios respectively, it is envisaged, as can be seen on Table 2. That renewable energy will contribute 17%, 19% and 20%, respectively, in meeting the total electricity demand in Nigeria on short, medium, and long terms scenarios.

If the contribution of large hydropower is discounted, the contribution of renewable energy would decline to about 5.6%, 7.7% and 16.6%, respectively, in reaching the national electricity demand under the 7% GDP growth rate. Furthermore, renewable energy is expected to make an average contribution of around 80% to non-electricity demand (Table 3). However, the average contribution is envisaged to decline over a period of time.

The estimated contribution of biofuels in meeting the demands for automotive fuels in the country is shown in Table 4. Transportation constitutes a greater part fuel demand in Nigeria. A robust public transportation system will help in curbing high demand of fossil fuel and reduction in carbon emission.

It should be noted that the solar energy policy states that government shall do all within its powers to

Table 3 Targets for non-electricity energy production (ECN, 2022)

S/N	ITEM	Short	Medium	Long
1	Thermal energy in (GWh)	194,000	202,000	249,000
2	Share of renewable energy (%)	86	81	80
3	Share of other non-renewable energy (%)	14	19	20

Table 4 Targets for Bio-fuel for vehicles at 7% growth (ECN, 2022)

Biofuel Type		Timeframe		
Bio-ethanol	Annual demand in billion litres	1500	2900	5700
	% contribution to PMS	10	10	10
Bio-diesel	Annual demand in billion litres	0.46	1	2
	% contribution to diesel	19.9	19.9	19.9

vehemently pursue the integration of solar energy into Nigeria's energy-mix. The major objectives shall be to develop and harness the nation's renewable energy capacity for purposes of efficient utilization of solar energy. The policy also states that Nigeria would use solar energy as the main energy source in rural and sub-urban areas that have the highest solar radiation in the country. The detailed solar development plan is shown in Table 5:

Energy demand and supply projections for nigeria

The Energy Commission of Nigeria carried out a holistic energy demand projection study based on Nigeria's government vision to industrialize Nigeria by the year 2030. The study estimated the amount of energy required for the transformation of the country from an agrarian economy to an industrialized nation by the year 2030 using the Model for Analysis of Energy Demand (MAED) that had been developed by IAEA. The economic and demographic features of industrializing countries were identified and applied in the model. The electric power demand projections by the government's Presidential Advisory Committee (PAC) were also adopted by the study.

The Nigerian government had anticipated growing the economy at a rate of 11% to 13%, the projection anticipates that Nigeria would be counted amongst the 20 biggest economies of the world by the year 2020 (Mansur, 2020)

Table 6 clearly shows the total share of energy demand by various sectors. For Reference Scenario, demands usually will differ from 1.15 Mtoe to 105.52 Mtoe, for the industry, 7.65 Mtoe to 28.51 Mtoe, transport, to 24.09 Mtoe; 46.29 Mtoe for households and 3.13 Mtoe to 10.67 Mtoe for the service sector in the planned period. The sector with the fastest growing rate is industry; viz-a-viz agriculture, construction, mining and manufacturing, with an overall yearly growth rates of 24.01%, 28.78% and 32.45% for the Reference, High and Optimistic Growth Scenarios, respectively. Energy demand in the manufacturing sector would have had the dominant energy demand, because energy utilization in the sector is by far more than those of agricultural, construction, and mining sectors.

In the same vein, the service sector will experience growth rates of 6.01%, 7.3% and 9.25% per annum, respectively; and transport by 6.46%, 7.49% and 7.88%; while the household will be growing at the rate of 3.16%, 4.85% and 4.68%, respectively, for the Reference, High and Optimistic growth scenarios. In the base year, households have the biggest share of energy demand at the rate of 66.9%, followed by transport, services and industry sectors which had the shares of 21.2%, 8.7% and 3.2%, respectively. Nevertheless, the structure is estimated to change significantly over the planned period.

A lot of projections were made by some very reputable consulting companies, notable amongst the projections made were JICA demand prediction of 2015, FIGHTNER projection in 2016, TCN energy demand forecast of 2012, and tractable forecast in 2019 (Yoshida, 2020). However, all of these forecasts were further studied by the Energy Commission of Nigeria to get them aligned with the energy demand scenarios in Nigeria. The diagrammatical representation of the projections is shown below (Fig. 2).

Power generation and energy mix

Studies have shown that Nigeria's current electricity grid cannot meet the country's energy demand, especially as its population continues to increase rapidly. It has also been discovered by studies that since the year of independence from colonialism in 1960, the electricity grid expansion has been rather quite slow when compared to the population growth rate. Nigeria, a country of about 40 million people in 1960, is well over 200 million as at 2020. Meanwhile, the grid and power generation expansion are nowhere near a commensurate ratio to its soaring population figures. Over the years, the electricity sector has been unbundled and privatized, yet, there is no significant improvement in power generation capacity. Many have linked the poor electricity generation and transmission to lack of gas supplies, while others blamed it on the deteriorating condition of the nation's electricity infrastructures, as well as poor maintenance culture. The generation, transmission and distribution capacity of the grid is shown in Fig. 3 below:

At present, Nigeria has an installed capacity of about 15 GW, however, due to maintenance issues, inadequate gas supply, water and transmission constraints, only about 3.9 GW to 6 GW is available for onward transmission to the grid via 25 hydro and gas-fired power plants which are mainly located in southern Nigeria (Failed, 2012b). The power generation sources include large and small hydro plants and gas thermal plants which account for about 85%, while hydro power accounts for 15%. Out of the 25 available power plants, 22 are gas thermal and 3 are hydro plants. The overreliance on fossil fuels has been the major problem

Table 5 Solar Development Plan (ECN, 2022)

Strategies	Activities	Timeline		
		S	M	L
(i) Increasing research and development in solar energy technology applications	(a) To painstakingly identify and develop local industries capacity in the design and development of solar PV technology, other technical expertise	*	*	*
	(b) Establishing regular trade fairs on solar PV innovations	*	*	*
(ii) Growing manpower and institutional capacity development in solar energy technology	(a) Encouraging collaborations among educational institutions—research institutes and centres with relevant international organizations	*	*	*
	(b) Encouraging competitive research grants on solar PV project proposals	*	*	*
	(c) Setting up professorial chairs on solar PV technology across various universities and other educational institutions in the country	*	*	*
	(d) Organizing both national and international conferences and workshops	*	*	*
(iii) Providing sufficient incentives to suppliers of solar energy products and services	(a) Developing and promoting market for solar energy products	*	*	*
	(b) Provision of market incentives such as feed-in tariffs for solar-powered appliances	*	*	*
	(c) Develop and ratify a legal pact on Power Purchase Agreements (PPA) with electricity generation and distribution companies	*	*	*
(iv) Providing enough incentives to local products manufacturers for the production of solar energy accessories				
	(a) Making available adequate grants for investment to encourage indigenous solar PV technology	*	*	*
	(b) Provision of tax holiday for local companies and organizations that are into solar PV technologies	*	*	*
	(c) Construction of solar PV and thermal plants for energy generation	*	*	*
	(d) Providing incentives to local and international investors to make investment in solar energy technologies such as production of solar panels and other components like inverters, batteries, and many more peripheral	*	*	*
	(f) The establishment of funds for renewable energy investments	*	*	*
(v) Introduction of measures to fast-track the development of local solar PV industry	(a) Introduction of relevant Policies, Legal and Regulatory framework to support solar energy industry	*	*	*
(vi) Establishing extension programs to promote solar energy technology to the rural and semi-urban communities	(a) Developing and siting of relevant pilot schemes	*	*	*
	(b) Training and retraining of extension workers on solar energy systems installation	*	*	*
(vii) Provision of fiscal incentives for the installation of solar power	(a) Introduction of tax incentives for solar panels and solar energy systems. Incentives can be in the form of free import duties, tax holidays, and so on	*	*	*
(viii) Aggressively engage in campaigns and advocacies on the utilization of renewables	(a) Sensitization of the public on the advantages of solar energy systems	*	*	*
(ix) Maintenance of an all-inclusive information system on available solar energy resources	(a) Conducting regular surveys to gather adequate information on solar PV technologies	*	*	*
(x) Development and enforcement of standards for solar PV technologies, equipment, and general services	(a) Assessment of global standards and practices on solar PV systems	*	*	*
	(b) Development and enforcement of internationally recognized standards for solar PV systems imported into Nigeria	*	*	*
	(c) Enforcement of safety standards for the development and installation of solar panels and other auxiliaries	*	*	*
(xi) Strategize on ways to access funds earmarked for the promotion of solar energy	(a) Identification and establishment of links and collaboration with OPS and other relevant international organizations	*	*	*

The "asterisk" was used to indicate the various scenarios for each of the items on the table

Table 6 Total energy demand projection by sector

Scenario and sector	Demand (Mtoe)						Growth RATE	% Share					
	2009	2010	2015	2020	2025	2030		2009	2010	2015	2020	2025	2030
Reference Growth (7%)	36	38	61	95	140	192	9	100	100	100	100	100	100
Industrial sector	1	1	23	47	74	106	24	3	1	38	50	53	55
Transport sector	8	9	12	16	21	29	7	21	25	19	17	15	15
Households	24	25	23	27	37	46	3	67	67	38	29	26	24
Service sector	3	3	3	5	8	11	6	9	7	5	5	5	6
High Growth Scenario 10%	36	37	75	125	201	347	11	100	100	100	100	100	100
Industrial sector	1	2	31	62	115	233	29	3	5	41	50	57	67
Transport sector	8	7	11	17	24	35	8	21	20	15	13	20	10
Households	24	27	30	40	52	65	5	67	72	40	32	26	19
Service sector	3	1	3	6	10	14	7	9	3	4	5	5	4
Optimistic Growth Scenario 13%	36	40	77	144	278	541	13.8	100	100	100	100	100	100
Industrial sector	1	7	35	82	190	421	33	3	17	45	57	68	78
Transport sector	8	6	11	17	25	38	8	21	14	14	12	9	7
Households	24	25	26	37	50	63	5	67	61	34	26	18	12
Service sector	3	4	5	9	14	20	9	9	9	6	6	5	4

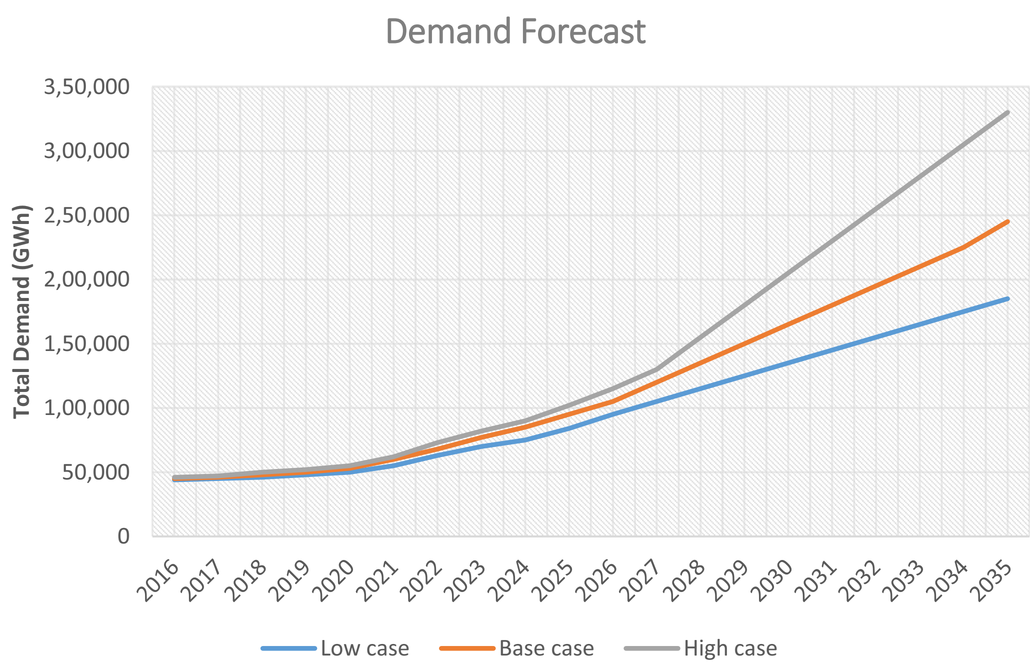


Fig. 2 National Demand Forecast (ECN, 2022; Mansur, 2020)

affecting Nigeria's energy supply, this development has been attributed to gas supply constraints, and inadequate power transmission and distribution infrastructures, as well as old and non-functional oil and gas facilities. Moreover, power generation capacity in most parts of the country from hydro plants during raining season (May to October), is about 80%. However, the generation capacity drops significantly to less than 50% during dry season. Furthermore, gas thermal power plants usually experience shortages in gas supply due to the criminal activities of oil thieves and the violent attacks on oil installations (Fig. 4).

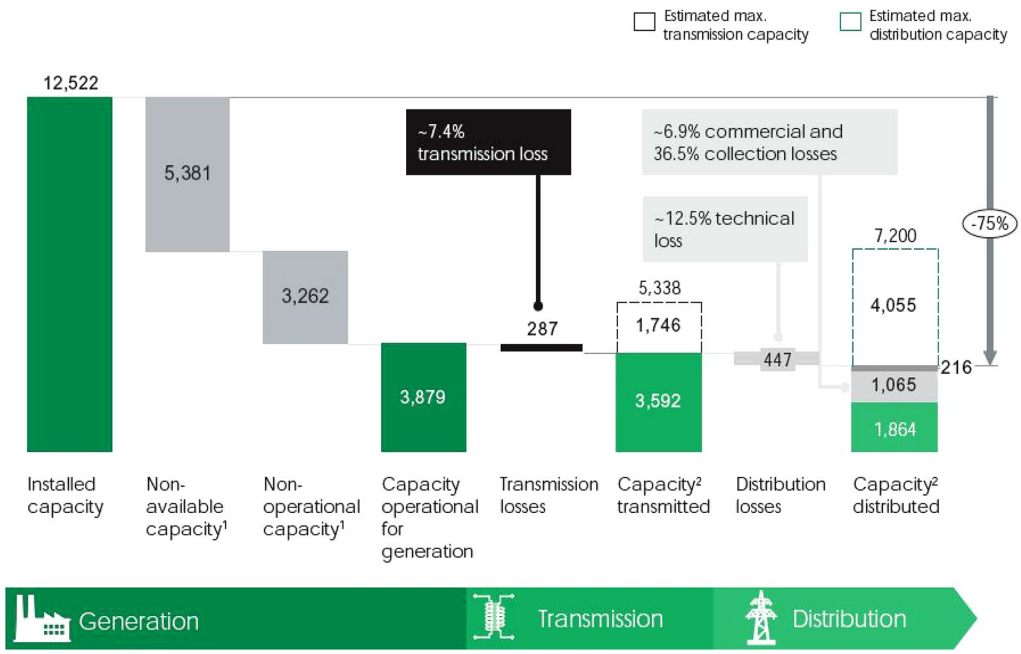


Fig. 3 An Overview of Nigeria's Power System

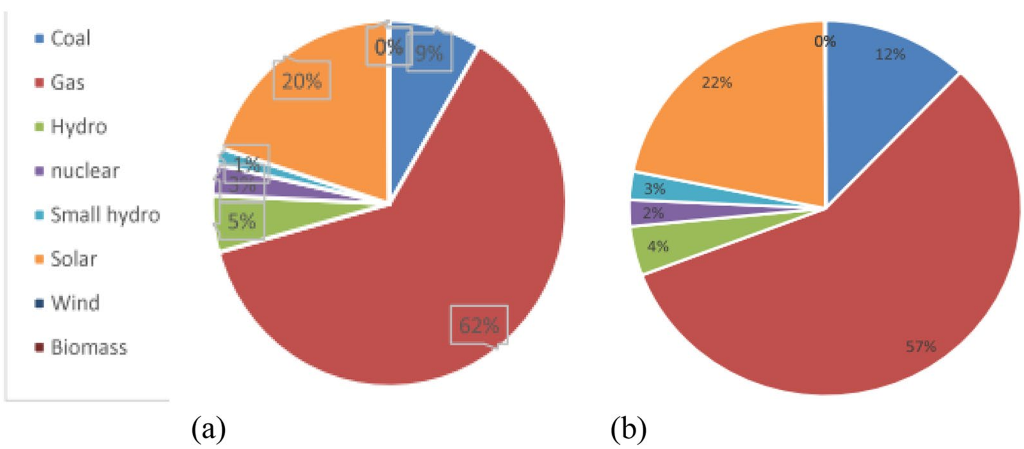
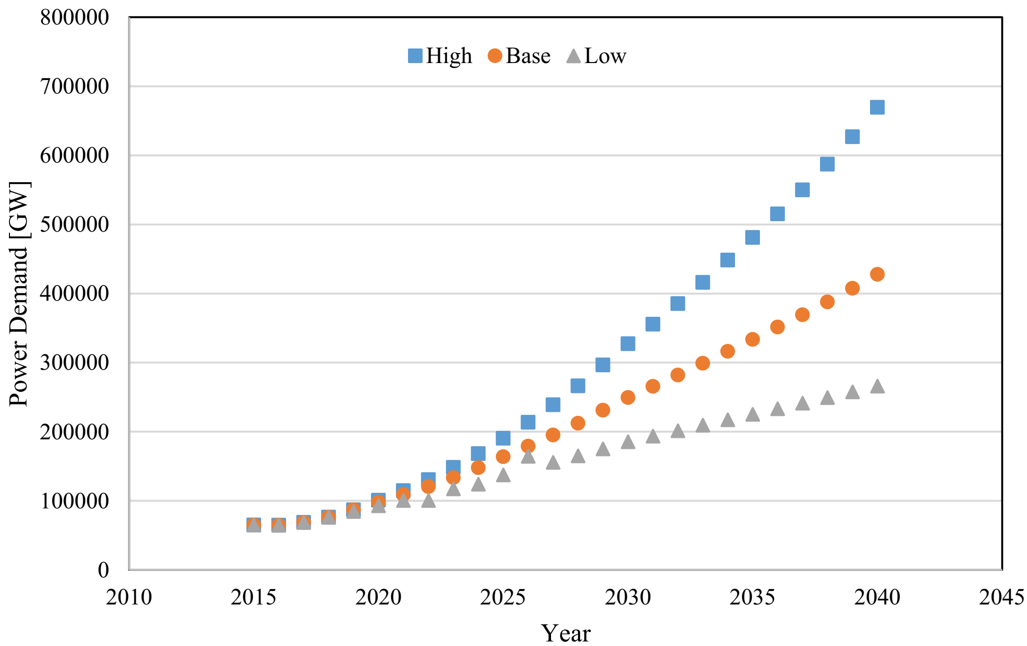


Fig. 4 Expected energy mix by (**a**) 2030 and (**b**) 2035 (ECN, 2022; Mansur, 2020)

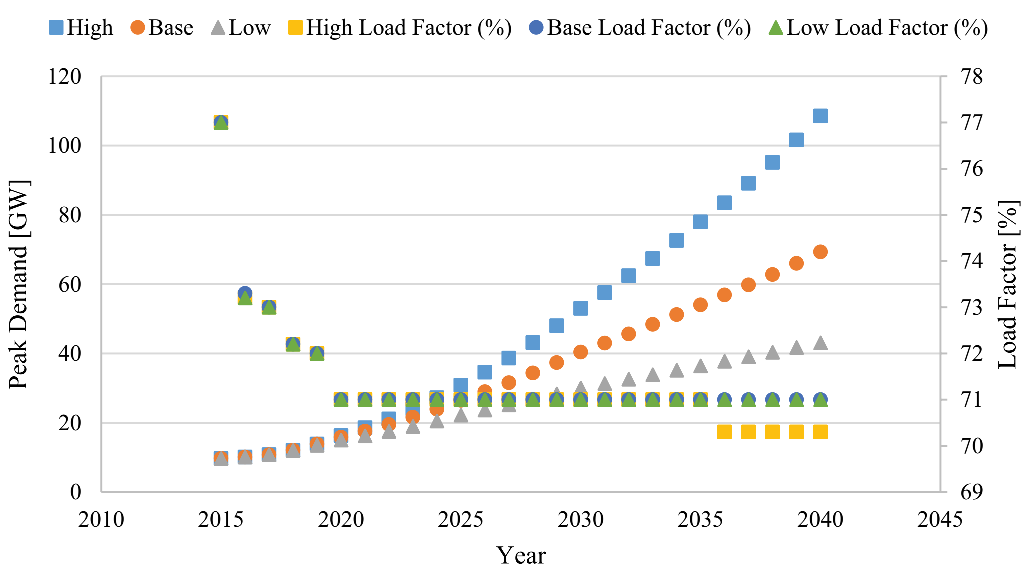
Load forecast and generation expansion plan

As stated in the previous section, demand forecasts were carried out by various consulting firms and then eventually reviewed by the Energy Commission of Nigeria. It was predicted using "Model for Analysis of Energy Demand" software (Mansur, 2020). The study analyzed future demand based on variables such as annual energy demand, population growth rate, and household size, etc. Based on the future economic prediction for 2030, three (3) load growth scenarios were developed to guide the study. The load growth cases are: low case, base case and high case. See Fig. 5 for details of the energy and peak load forecasts for each case:

Considering the fact that there is an already forecast demand information available, the main target under electricity generation expansion plan is to identify the optimum energy mix that would provide the lowest marginal cost for power generation. The forecasts are shown in Table 7 for the low scenario installed capacity, Table 8 for the base scenario installed capacity and Table 9 for the high scenario installed capacity. The



(a)



(b)

Fig. 5 The Nigeria's energy demand forecast (**a**) power demand and (**b**) peak demand with corresponding load factor

two (2) aspects of marginal costs applied were Short Run Marginal Cost (SRMC) and Long Run Marginal Cost (LRMC) (Mansur, 2020). In this case, a marginal cost simply means the cost of producing an additional unit of electric energy. Optimal generation expansion occurs only when SMRC equals LRMC (Table 10)

Planning policy implemention

Given the interrelationships between energy demand and supply, and the environmental issues that surrounds energy utilization and pollution into the atmosphere, there is need for proper and efficient energy planning. Any nation that is serious about meeting its short- and long-term energy needs, must put in place a very

Table 7 Installed Capacity for Low Scenario, GW (ECN, 2022)

	2009	2010	2015	2020	2025	2030	2035	2040
Coal	0	0.61	1.80	6.53	7.55	10.98	18.68	20.00
Electricity	0	0	0	0	0	31.95	39.64	42.42
Gas	3.8	4.57	18.68	33.71	61.89	80.56	88.25	94.43
Hydro	1.9	1.93	3.04	6.53	6.53	6.53	6.53	7.00
Nuclear	0	0	1.00	1.50	2.50	3.50	3.50	3.75
Small hyd	0.02	0.06	0.17	0.41	0.89	1.89	3.77	4.04
Solar	0	0.26	1.37	3.46	7.00	25.91	33.62	35.97
Wind	0	0.01	0.02	0.02	0.03	0.03	0.03	0.04
Biomass	0	0	0	0.02	0.04	0.05	0.06	0.06
Total	5.7	7.4	26.1	52.2	86.4	161.4	194.1	207.7

Table 8 Installed Capacity for Base Scenario, GW (ECN, 2022)

	2009	2010	2015	2020	2025	2030	2035	2040
Coal	0	0.87	2.58	9.32	10.78	15.69	26.62	29.28
Electricity	0	0	0	0	0	45.64	56.57	62.23
Gas	3.8	6.96	21.33	44.76	82.70	115.09	126.02	138.62
Hydro	1.9	2.17	4.35	9.33	9.33	9.33	9.33	10.27
Nuclear	0	0	1.50	2.50	3.50	3.50	3.50	3.85
Small hyd	0.02	0.08	0.25	0.59	1.28	2.99	13.92	15.32
Solar	0	0.38	1.96	4.94	10.00	37.03	47.96	52.75
Wind	0	0.02	0.03	0.03	0.04	0.04	0.05	0.05
Biomass	0	0	0	0.02	0.05	0.08	0.08	0.09
Total	5.7	10.5	32.0	71.5	118.0	229.1	284.0	312.5

Table 9 Installed Capacity for High Scenario, MW (ECN, 2022)

	2009	2010	2015	2020	2025	2030	2035	2040
Coal	1	3354	3354	12,123	14,012	20,400	35,096	40,009
Electricity	1	1	1	1	1	59,334	74,030	84,394
Gas	3804	13,111	26,427	49,997	120,513	164,308	179,004	204,064
Hydro	1931	4158	11,208	12,133	12,133	12,133	26,829	30,585
Nuclear	1	1	3600	7201	7201	7201	7201	8209
Small hyd	21	106	321	761	1661	3503	18,199	20,746
Solar	1	500	2544	6418	15,971	48,133	62,829	71,625
Wind	1	24	37	42	48	55	61	69
Biomass	1	1	6	31	66	101	111	126
Total	5762	21,247	47,499	88,707	171,607	315,167	418,056	476,583

effective and robust energy policies to grow every facet of the economy.

For an effective planning, attention must be given to both past and present energy consumption patterns. This will guide any future projections as well as provide the necessary information upon which a short- and long-term plan can be made. It is primarily a way of knowing the energy demand–supply trends of a society upon which future decisions could be made about investment strategies, energy utilization patterns, and formulation of relevant economic policies (Ubani et al. 2013).

Table 10 Action plan for energy planning (ECN, 2022)

Strategies	Activities	Timeline		
		S	M	L
(i) Ensure a formidable relationship between ECN and other stakeholders within the energy sector in Nigeria	(a) Intensifying formal collaborative partnership	*	*	
(ii) Encourage cooperation between government parastatals and other relevant institutions in the energy sector, especially those with related organizational mandates	(a) Intensifying formal collaborative partnership	*		
(iii) Facilitate the development of energy planning sections at the state level and also encourage giving responsibilities on energy matters to the authorities at the local government	(a) Establishing at the state level, an energy planning and implementation units	*	*	
(iv) Making sure that energy plans and programs at the sub-sectoral level are evaluated in order ensure consistency with national policy	(a) Carrying out an integrated energy planning and implementation study	*	*	*
	(b) Ensuing that results of energy planning study are presented to the relevant stakeholders	*	*	*
(v) Encourage the establishment of a national energy information platform where data analysis is carried out and available for stakeholders in the industry to facilitate an informed decision-making	(a) Ensuring that the national energy information platform is strengthened	*	*	*
	(b) Ensuring an accelerated development of a national energy database	*	*	*
(vi) Making available energy data for relevant government agencies to help them carry out their monitoring and evaluation responsibility as assigned by the government. The Energy Commission of Nigeria, Transmission Company of Nigeria, Nigeria Electricity Regulatory Commission, etc. are some of the relevant organizations that may require energy data and information from time to time	(a) Ensuring an accelerated development of a national energy database	*	*	*
	(b) Providing energy database for energy planning and implementation strategies	*	*	*
(vii) Development of an energy master plan that is based on empirical study on energy demand and supply trends in the country	(a) Ensuring an accelerated development of a national energy masterplan	*		
	(b) Presentation of energy masterplan to relevant stakeholders in the energy sector	*		
	(c) Presenting the energy masterplan to FEC for proper review and final endorsement	*		
	(d) Encouraging effective monitoring, and periodic reviewing of the energy masterplan	*	*	*
(viii) Ensuring the development of strategies for a robust manpower training and capacity development in the energy sector	(a) Development for evaluation strategies for taking stock of manpower needs in the industry	*	*	*

The "asterisk" was used to indicate the various scenarios for each of the items on the table

Energy policy planning in Nigeria is handled at four various levels of authority. These are: National level, Sectoral level, Sub-sectoral, and Operational level. The federal ministry of budget and planning is responsible for policy implementation as regards to multi-sectoral developmental approach. The sectoral level of authority deals with the overall planning and implementation of energy policy. It makes sure that there is consistency and coherence in energy policies at the sub-sectoral level. While the sub-sectoral level handles a more specific energy planning and implementation strategies to explore, exploit, and utilize energy resources. Part of the sub-sectors are oil and gas, solid minerals, electricity, nuclear energy technology, transport, industry, agriculture, research and development, household, etc. (Igbinovia & Tlusty, 2014). Activities involving policy execution and implementation of plans developed by the sub-sectors are done at the operational level. Some of the establishments involved in such implementations are those that carry out oil explorations, oil production and marketing, power generation, transmission and distribution, and so on. Of course, no policy can be said to be successful without an effective implementation. Furthermore, to effectively implement any energy policy, there must be effective strategies to monitor and evaluate its implementation process to ensure that the implementation guideline is followed to the letters, and also ensure that amendment is made where and whenever necessary.

Monitoring and evaluation make it possible to:

- Measure and ascertain progress in achieving the policy's main goals and objectives.
- Monitor inputs and outputs during implementation process.
- Find out if the implementation is being carried out according to the masterplan.

- Identify any existing or potential challenges even before they become a big problem.
- Constantly review of the strategies and also make corrections where necessary, so as to ensure that inputs are in conformity with expected outputs.

Parameters were set in place to monitor and evaluate achievements spelled out in the masterplan for each type of energy. All performance variables can be easily compared with targeted values which were spelled out on short, medium or long-term scenarios. Table 14 shows the detailed action plan for energy planning and policy implementation (ECN, 2022).

In the case of policy implementation, the national energy policy shall be the reference point for its implementation to ensure consistency with national planning. The Energy Commission of Nigeria is the focal institution for the coordination, monitoring and evaluation of energy policy and implementation strategies at all levels of governance.

Literature review

Machine learning

Over the years, machine learning (ML) has been applied to various academic areas and fields in solving data related problems. Machine learning techniques cut across a vast variety of fields such as statistics, engineering, mathematics, computer science, artificial intelligence, data mining, etc. The algorithms utilized in machine learning usually tend to determine the relationship that exists between input and output. For appropriate decision-making, a forecasting input dataset is fed into a model, after the model has been trained using a training dataset. Data pre-processing technique is very vital for machine learning performance. It helps the model to perform optimally (Hwang & Kim, 2020). Normally, machine learning algorithms utilize three (3) learning methods, namely, supervised, unsupervised, and reinforcement learning. Based on these three learning principles, there have been many theoretical strategies that have been proposed for the application of machine learning for forecasting (Malik & Kuba, 2013). Deep learning, which is a sub-set of machine learning, has been gaining popularity in recent times due to dynamic nature of information technologies (Alzubaidi et al., et al. 2021; Choudhary et al., et al. 2022; Pichler & Hartig, 2023; Sarker, 2021). Many machine learning studies used in forecasting renewable energy have been done using a just one machine learning model. However, due to the dynamisms in datasets, influenced by weather information, time steps, and other settings, it is difficult to achieve a good accuracy using just a single machine learning model. It, therefore, takes the combination of different models to get an optimum forecasting performance. Hence, to achieve an optimum performance in machine learning, some methods such as support-vector machines and deep learning methods were developed for energy predictions.

Application of machine learning to renewable energy prediction

Table 13 lists some recent survey studies where machine learning algorithms have been applied for energy prediction. Swisher et al. (Swisher et al., et al. 1997) reviewed literature on photovoltaic power prediction using artificial intelligence, deep learning, and hybrid technique. The authors established that when using weather datasets for predictions, Long Short-term Memory (LSTM) model, Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) can be utilized for optimum performance. They also estimated the time-dependence data in solar PV power forecasting. In their recent studies, Kotsiantis (Kotsiantis, 2007) reviewed power prediction techniques based on deep learning. In their studies, the authors classified the prediction techniques into four, namely, deep belief networks, stack auto-encoder, deep recurrent neural networks, and others. They utilized data pre-processing techniques to the prediction accuracy. Qiu et al. (Qiu et al., et al. 2016) investigated artificial neural networks in predicting renewable energy. Energy sources in this research include solar PV, hydropower, and wind. Many scenarios were made available to establish that artificial neural networks performs better than other conventional methods in energy forecasting. Wang et al. (Wang et al., et al. 2019) carried out a survey on the application of machine learning techniques in energy systems. The authors' findings were very instrumental to designing a well-performing machine learning model. Abdalla et al. (Abdalla et al., et al. 2021) also investigated prediction models of renewable energy considering energy storage, energy policy, electricity market, power systems, and optimal reserve capability. The review was very important to the energy sector because it enumerated the recent trends in power prediction and ways of improving power systems operations. Furthermore, Zendehboudi et al. (Zendehboudi et al., et al. 2018) investigated the application of support-vector machine learning models in predicting solar and wind energy. The study showed that support-vector machine models performed better than other models in prediction accuracy. Also, the authors revealed that a combination of different support-vector machine models is capable of obtaining a much accurate result than support-vector machine with a single model. Jesús et al. (Jesús & F., G.F.J., Fernando, O.P., & Adolfo, C.M., 1844) conducted a study on machine learning performance and forecasting procedures in solar

PV power generation. The study showed that using ANN and support-vector machine model has been thriving in renewable energy studies. The authors explained that differences in whether conditions cause errors in the prediction of solar power, because solar radiation, humidity and temperature are major variables that affect solar energy. Howland and Dabiri (Howland & Dabiri, 2716), did a review on the utilization of machine learning models in forecasting solar radiation. The study indicated that ANNs, support-vector regression, regression tree, and gradient boosting are veritable tools for solar radiation prediction, and hybrid model approaches are reliable techniques for improving the accuracy of prediction.

Renewable energy is a clean source of energy. As an environmentally friendly energy source, it helps in combating the negative effects of climate-change. Renewable energy is a veritable alternative to fossil fuels. However, it has certain features that makes it not to be a year-round reliable energy source. Its intermittency is one of the disadvantages associated with it. For example, solar energy depends heavily on solar radiation. There won't be energy without sunlight. This means that during periods when sun rays are not available such as during rainy season, there will not be enough solar radiation to provide energy. This is why the need for the prediction of renewable energy using an accurate forecasting technique is imperative. Machine learning is a reliable forecasting technique for energy prediction using whether datasets and other deep learning structures to obtain an intelligent output. In an extensive research, Demolli et al. (Demolli et al. 2019) divided machine learning models for energy prediction into three; namely, statistical models, artificial intelligence, and hybrid technique. The study gathered and analyzed 130 recently published papers on renewable energy resources. The seven renewable energy sources analysed in the study are solar, wind, hydro, biomass, wave, tidal, geothermal. Solar energy constitutes 43% of the total renewable energy sources reviewed in the literature, wind energy source makes up nearly 40%; while all of the remaining five energy sources were less than 5% each.

Parameter selection of machine learning models

The selection of parameters influences the performance of machine learning models a lot (Li et al., et al. 2019). Many ML models have more than two parameters. Therefore, metaheuristics has been a common medium of seeking proper parameters of a ML model. Primarily, predicting error functions is the basis for objective functions for optimization using metaheuristics (Feng et al., et al. 2017). To make predictions, a new set of parameters is generated by a machine learning model for every single iteration. As a result, a new forecasting error is generated. At times, a validation dataset is separated from the training dataset to the problem of overfitting. Lahouar and Ben Hadj Slama (Lahouar et al., et al. 2017) used the Gray Wolf Optimization (GWO) technique to select conjunction parameters of the ANFIS model in predicting power generation in a hydropower plant. The GWO is able to improve the forecasting performance of ANFIS significantly (Andrade & Bessa, 2017). Also, an Improved Moth Forecasting Optimization (IMFO) algorithm can be utilized in optimizing the parameters of the SVM model in forecasting solar PV power generation. Figure 6 displays a collection of metaheuristics for the selection of machine learning parameter for energy prediction.

Leva et al. (Leva et al. 2017), in their study on predicting solar energy generation using artificial neural networks, conducted sensitivity analysis to evaluate the model performance. Using perhaps the simplest approach, the model was evaluated on the same problem with, but a different size of dataset. This allowed the training dataset and test dataset to increase with the size of dataset. It is generally expected that the mean model performance will increase with dataset size, while the uncertainty in model performance will decrease with dataset size.

Results may be different, given the stochastic nature of the algorithms or evaluation process. Consider running the example a few times and make a comparison of the result generated. Specifically, there would be an improved performance with more dataset rows, however, this relationship can be captured with small variance using 10,000 rows of data or more (Khan et al. 2229). This situation may be the upper limit on the model performance. Which means that there is every likelihood that an increased dataset would not result to an improved performance of the model. These findings may be used as the benchmark for testing other model structures or a different type of model (Fischetti & Fraccaro, 2019; Ma & Zhai, 2125; Mujeeb et al. 2019). The problem here is that different models will perform differently depending on the size of datasets. Therefore, the best approach will be to conduct the sensitivity test with a different model to see if the relationship actual holds (Harbola & Coors, 2019).

Measurements of forecasting performance

In this section, prediction accuracy measurements are reviewed. Tables 11, 12 show the prediction accuracy measurement that was conducted by 10 different studies. Some of the most often utilized measurement of forecasting error for energy prediction are Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Square Error (MSE) (Alsharif et al., et al. 2019; Aslam et al., et al. 2020; Li et al., et al. 2022). There are different units with which renewable energy can be

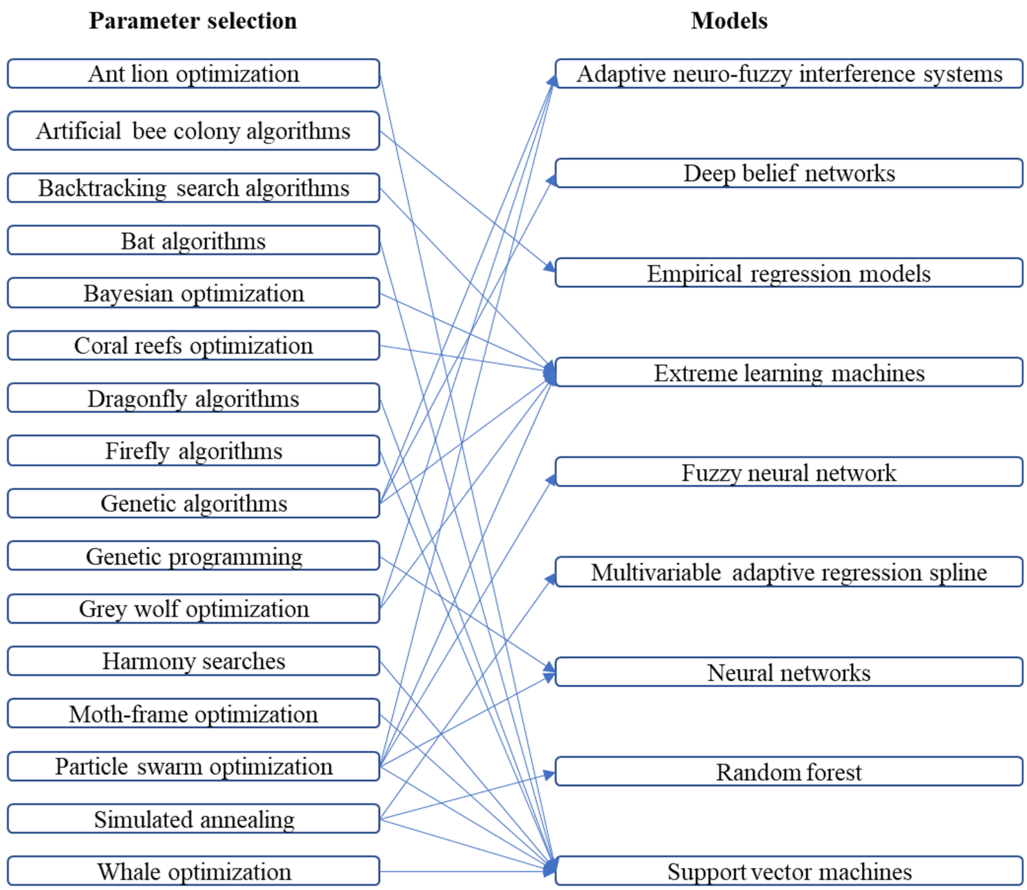


Fig. 6 Metaheuristics for ML parameter selection in renewable energy predictions (Khosravi et al. 2018)

Table 11 Review of Measurement of Forecasting Accuracy (Ma & Zhai, 2125)

Energy source Measurements	Solar	Wind	Hydro	Bio mass	Geo thermal	Wave	Tidal	Total
MAE	18	27	2	4	2	3	1	57
MAPE	13	24	1	2	1	1	4	46
RMSE	37	32	2	5	1	3	4	84
R2	10	9	2	4	2	2	1	30
NRMSE	10	5	1	1	1	1	1	20
MSE	3	9	1	2	2	1	1	19

represented, and the values changes for different analysis conducted. To prevent the effects of units and values of renewable energy, mean square error (MSE) is utilized in this study to depict forecasting accuracy. According Kim et al. (Kim et al., et al. 1501), MSE values of less than 1000 are acceptable accuracy in prediction. Thus, most of the forecasting accuracies in the literature review have high MSE. Furthermore, another measurement of forecasting error identified in this study is coefficient of determination (R^2) (Failed, 2018; Saloux & Candanedo, 2018; Torres-Barrán et al., et al. 2019; Zambrano & Giraldo, 2020). The coefficient of determination explains the relationship that exists between the dependent variable that is explainable by the independent variables. The lesser the variation between the dependent variable and the independent variables, the better (Khandakar et al., et al. 2782; Rodríguez et al., et al. 2018). This means that a high coefficient of determination explains

Table 12 Structure of Neural Network

Input	Ulsan real-time dataset
Learning	Optimizer = 'adam', loss = 'mean_squared_error' Learning rate = 0.07 Batch size = 150 Verbose = 1 Validation split = .2
Hyper Parameters	Scaler = Min_Max Scaler (feature_range = (0, 1)), Standard Scaler Train-test split ratio = Training size (0.8), Test size (0.2) Cov_mat = (14, 14) Number of iteration = 30 epochs Matrix = 'MAE', 'MSE' Layers = Dense, LSTM Units = 50 Loss = Mean Squared Error
Output	Predicted result image (14, 50) shape

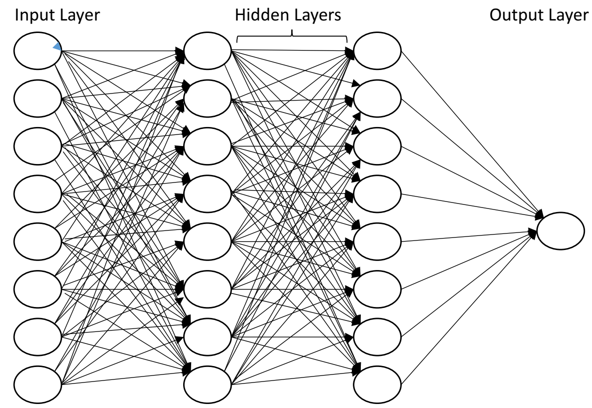


Fig. 7 Recurrent Neural Network

that a significant relationship exists between dependent variables that is explainable by the independent variables (Leva et al., et al. 2017). Therefore, this study showed that machine learning models with high coefficient of determination (R^2) result in more accurate prediction using mean square error (MSE) (Sun et al., et al. 2019). It is advisable to first calculate the coefficient of determination when conducting machine learning before continuing with building of the model for renewable energy prediction. A hybrid model containing empirical wavelet transform, long short-term memory network, and Elman neural networks (EWT-LSTM-Elman) was proposed and outperformed the other forecasting models in windspeed predictions (Alpaydin, 2004; Hristev, 1998).

Techniques for data preprocessing

When building a model for energy forecasting, the process of modeling can be divided into four; these are: data preprocessing, model training, testing, and output forecasting. Data preprocessing involves removal of missing dataset values. Missing datasets values are as a result of lack of data necessitated by some abnormalities in data collection procedures. For instance, solar radiation data at nighttime have no meaning in solar-power forecasting. Therefore, missing data must be removed through data preprocessing technique to facilitate accuracy in energy prediction. Several preprocessing procedures for machine learning models exist. Machine learning models utilize these techniques for prediction of renewable energy such as solar PV, wind, hydro, etc. The most often used method is the decomposition method. Data splitting is also part of preprocessing procedure where machine learning model splits an original data into training dataset, validation dataset, and test dataset. The kernelized Mahalanobis distance (kWMD) method can be used to accurately estimate the similarities between two unknown sets of sample (Failed, 2017). To increase forecasting accuracy, data decomposition can be utilized. It is also used to preprocess the original signal. Furthermore, a dataset with high dimension can be decomposed into a low dimensional dataset using data decomposition technique. This technique is also often utilized in analyzing signal processing problems.

Converting discreet data to continuous data is very important in renewable energy forecasting using weather datasets. The coding automatically removes every missing value, redundancy, and data exceptions from the original dataset, thereby creating a more accurate characteristic that shows the relationship that exists between the dependent variable and independent variables, as well as between problems and prediction models. In the same vein, feature selection is a methodology used in finding proper independent variables to get rid of any undesirable data attributes. Meanwhile, imputation of dataset's values is the process of replacing values that are missing when found during the process of modelling (Dekking et al. 2010). The process of adjusting datasets which are given in varied scales so that they can be effectively processed by a machine learning model is called data normalization techniques. For instance, weather data attributes have to be normalized when analyzing or predicting speed of wind. Finally, data standardization is the process whereby data of different size units are converted to the same size. To measure dataset scales, Z-score values are utilized (Lee & J.y., 2019; Szegedy, 2015).

Methodology

Overview of research strategy

The long short-term memory (LSTM) is the deep learning approach that has been utilized for data analysis and solar power prediction in this study. Figure 7 shows a diagrammatical representation of a recurrent neural network. Neural networks are the building block of LSTM. Just as its name "neuron" implies, artificial neural network (ANN) was patterned after the human's neurological make-up. It is normally built by imputing neurons into layers and placing the multiple layers amidst input and output layers. To each input value, multiplication factor is applied, and then the weighted average of input is calculated. Afterwards, the total value is sent via an activation function for non-linear transformation. The LSTM model is a very good model for the prediction of renewable energy. The model has been discovered to be one of the best deep learning models available for accurate prediction of energy (Jason, 2018; Nam et al., et al. 2019). One of the advantages of the LSTM is that it has a large variety of parameters such as input biases, learning rates, etc. It does not require adjustments. Moreover, the complications associated with updating each weight are drastically reduced and is a special type of recurrent neural network (RNN) that has the ability to learn long term data dependency.

The artificial neural networks (ANNs) are patterned in such a way that it is comprised of nodes, having an input layer, with at least one or two hidden layer(s), as well as an output layer. All the nodes or neurons get attached to each other and has a concomitant weight and edge. Once the output of the nodes is more than the edge's specified figure, the node would be activated, and then sends data to the next layer. This process is repeated until the learning procedure is completed.

Neural network depends on trained datasets to learn and improve its prediction capability. Nonetheless, once the model algorithms are modified, they become a potent tool for renewable energy prediction, as well as in computer science and artificial intelligence; enabling users to classify and cluster datasets in a rapid speed. Consider each node as a linear regression model that stands on its own, comprising input dataset, weights, biases, and output. Mathematically, it can be expressed thus:

$$\sum_{i=1}^{m} wixi + bias = w1x1 + w2x2 + w3x3 + bias$$

$$output = f(x) = \begin{cases} 1\, if \sum w1x1 + b \geq 0 \\ 0\, if \sum w1x1 + b\, 0 \end{cases}$$

As soon as the layer for input is determined, the weights are then automatically assigned. The weight helps in determining the relevance of every variable, with the larger ones making significant contribution to the output compared to other inputs. All the inputs are then multiplied by the weights and then finally summed up. Subsequently, the input is sent via an activation function, which eventually defines the output (result).

Method of data collection and analysis

The datasets for the study are Nigeria's weather data gathered from NASA database for the cities named Abakaliki, Awka, Enugu, Owerri, and Umuahia. The deep learning (LSTM) algorithm was utilized to analyze an hourly weather dataset for two consecutive years (January 1, 2019 to December 31, 2020) which were gathered from NASA database. The datasets comprise of date/time, solar azimuth angle, temperature, humidity, wind speed, wind direction, cloud and power; with power being the dependent variable. The climatic condition of the states under study is largely tropical climate. In most days of the year, there is usually significant rainfall in the states. The states have only a short period of dry season, and the average daily temperature is 26 °C, with about 2679 mm of precipitation falls annually.

Geographical information of the five cities

Abakaliki is located on latitude 6.311o and longitude 8.112o at the northern flank of Southeast, Nigeria. As in NASA's database, the nominal power of the PV system (c-Si) (kWp) = 1.0, with an azimuth angle of 27°, the elevation is 53 m, while the PV system losses = 14%, and the slope is 11°.

Awka is located on latitude 6.208o and longitude 7.075° in Southeast, Nigeria. The nominal power of the PV system (c-Si) (kWp) = 1.0, with an azimuth angle of 28°, the elevation is 112 m, while the PV system losses = 14%, and the optimum slope is 11°.

Located on latitude 5.492° and longitude 7.032°, Owerri is a region at the southern flank of Southeast, Nigeria. From the analysis, solar radiation in the region is less than most of the regions selected for this study. Also, energy consumption in the region is relatively lower than that of Awka, Enugu, and Umuahia regions.

For Umuahia, the nominal power of the PV system (c-Si) (kWp) = 1.0, the azimuth angle is 33°, the elevation is 155 m, and the PV system losses = 14%.

Enugu city has an average peak sun hour of 4.5 h/day, making it a competitive choice for solar power investment by both the government and private investors. The area is located on latitude 6.449° and longitude 7.510° eastern Nigeria.

Building and training of lstm optimal model

The study has been conducted to use machine learning to accurately predict solar power generation and of five different states in Nigeria. The study ascertained the reliability of deep/machine learning algorithms in predicting daily solar power generation in these states. This approach helped to identify the state with the highest solar energy potential and recommend as the first point of call for solar power investment. The Keras library was used to facilitate fast experimentation and prototyping. It is a high-level neural network for building and training deep learning models. Keras can run on several platforms such as tensorflow, theano, and so on. To create and fit the neural network, we initialized a sequential model, afterwards we added an LSTM and dense layers to the model. The model was compiled, and then we trained the model using the training dataset. The training dataset was a real-time data collected from a solar generation plant in Ulsan, Republic of South Korea.

The algorithm developed to determine the optimal model used for the analysis, including the regularizer, the activation function, optimizers is:

missing values from the data frame, isnull() function was utilized. These two functions help in verifying if a weather data value is NaN or not. The function was also utilized to identity and remove null values in pandas' library.

Python provided arrays of functions used for analyzing times and seasons and converting it into a better data frame more suitable in python. Python programming language handled dates and seasons in diverse ways. Date formats were converted easily in python. Time and calendar modules of python were used to track time and dates. Many of the time functions in python handle time as a tuple of nine-digit numbers, while some tuples are equivalent to struct_time structure. The structure used for this study, has these attributes: tm_year, tm_mon, tm_mday, tm_hour, etc.

```
EPOCHS=30
from itertools import dropwhile
from keras import regularizers
# create and fit the LSTM network
model = Sequential()
# x_train.shape[1]  timestep
model.add(LSTM(units=50, kernel_regularizer=regularizers.l1(l1=1e-4),return_sequences=True, input_shape=(x_train.shape[1],x_t
model.add(LSTM(units=50,kernel_regularizer=regularizers.l1(l1=1e-4), return_sequences=False))
#model.add(Dropout(0.1))
model.add(Dense(1))
early_stop=keras.callbacks.EarlyStopping(monitor='mse', patience=5)
model.compile(loss='mean_squared_error',optimizer='adam', metrics=['mae','mse']) #optimizer=rmsprop10

#keras.callbacks.EarlyStopping(monitor="val_loss", patience=5, verbose=1)
model.summary()
```

LSTM Optimal Model

Data preprocessing

Data preprocessing is the process of converting existing data into data suitable for machine learning algorithms. This preprocessing process was applied to the five cities datasets to enhance the performance of the model learning. The data preprocessing employed in this study are loading of data, checking missing data, processing missing data, converting date and time-related data, separating training and test dataset, verifying data, checking the correlation and multi-collinearity, removing inappropriate data, and scaling the data. Figure 8 shows the covariance matrix of correlation coefficients.

Removing missing values is a major part of data preprocessing procedure. In checking and removing the

The correlation coefficient measures the relationship that exists between the dependent variable and the independent variables in the set of data. This measurement is very important in the field of science and engineering, and python programming language was used as a formidable tool to estimate correlation coefficient. Every dataset uses variables and observations. When data are presented in a tabular format, the table's rows contained the observation, while the columns are the features.

Also, number scaling in machine learning is a common pre-processing procedure to normalize and standardize numbers that are of different units of measurement. The independent characteristics that is present in the dataset was normalized through number scaling process. Scaling results in a new sequence such that an entire value in a

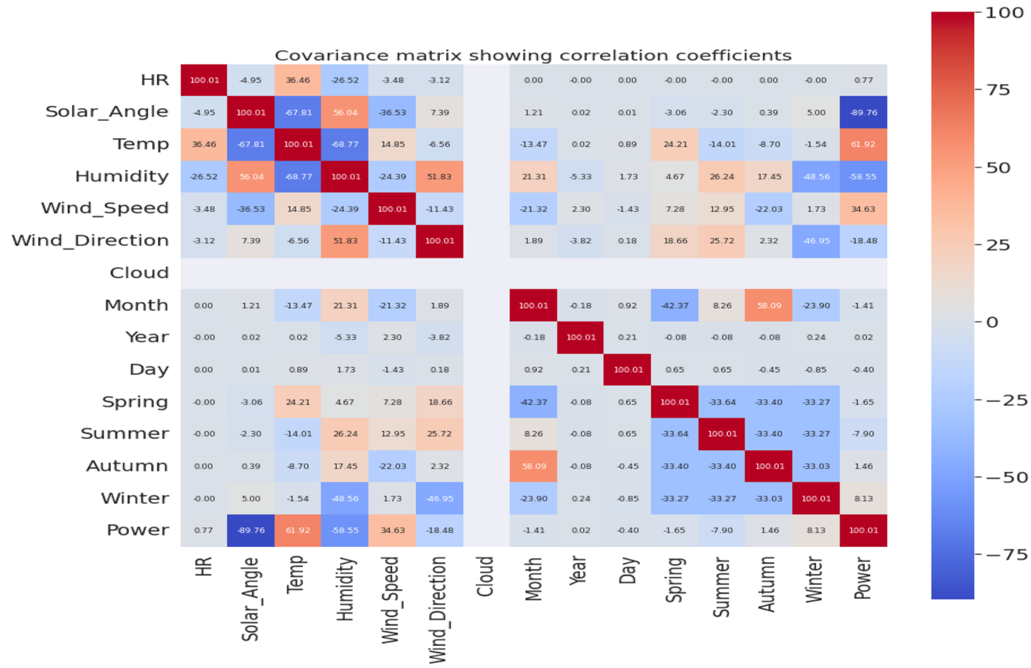


Fig. 8 Covariance matrix showing correlation coefficients

column comes under a range when applied to a python sequence like pandas series. For example, if the range of a given dataset is between 0 and 1, then all the sets of data within the column were normalized and changed within 0, 1 range only. If the dataset sequence were (AfDB, 2019; IRENA & CPI, 2023; Pierce & Roux, M.l., 2023), then the entire dataset was sequenced in the range of [0, 0.5, 1]. Similarly, scaling enhanced the merging speed of different algorithms in the machine learning. In this study, Scikit-learn was used to scale the pandas' data frame.

Validation of the neural network

To validate and ascertain the accuracy of prediction, dataset from the Ulsan area, Republic of Korea was first collected and analyzed using deep learning. The Ulsan dataset was a real-time dataset gathered from a solar generation plant in Ulsan. Machine learning was conducted to train the neural network and determine the accuracy of the model for power prediction. After training the data from Ulsan area, the model performance was good with 0.032 validation MSE and 0.050 training MSE. The excellent prediction of the model indicates that the model could be applied to the datasets of the five cities in Nigeria considered in this study. The neural network was then applied to the datasets of the 5 cities. Each city's dataset was entered into the neural network that was trained using Ulsan dataset. The predicted result showed different solar energy generation potentials for each city.

Meanwhile, to know if machine learning method is better than conventional method of solar power prediction, a conventional method of prediction was used to analyze the same dataset. The conventional method was analyzed by excel spreadsheet using forecasting method of energy prediction. It was discovered that ML method as shown in Fig. 9c is better, because its accuracy is higher than conventional method shown in Fig. 9d. Quantitatively, with an input data of 14,024 the use of the deep learning method results in MSE of 0.01 and R2 value of 0.92. Meanwhile the conventional approach results in the MSE of 0.43 and R2 value of 0.41. This indicates that the conventional approach deviated significantly from the mean. This step was taken to justify the use of ML over conventional method of solar power prediction.

Results and discussion

Solar power generation analysis using abakaliki dataset

Figure 10 shows the result of the predicted power (kW) from Abakaliki region in comparison with the actual data from NASA's database. The predicted result shows a significant difference with the actual. The actual data were analyzed conventionally using solar radiation data from the target city. Owing to the difference that exists between it and the predicted result from the neural network trained by Ulsan dataset which was a real-time data from a solar generation plant in Ulsan, South Korea, it is expected that the ML prediction would present a more reliable data for policymakers in the targeted region. The

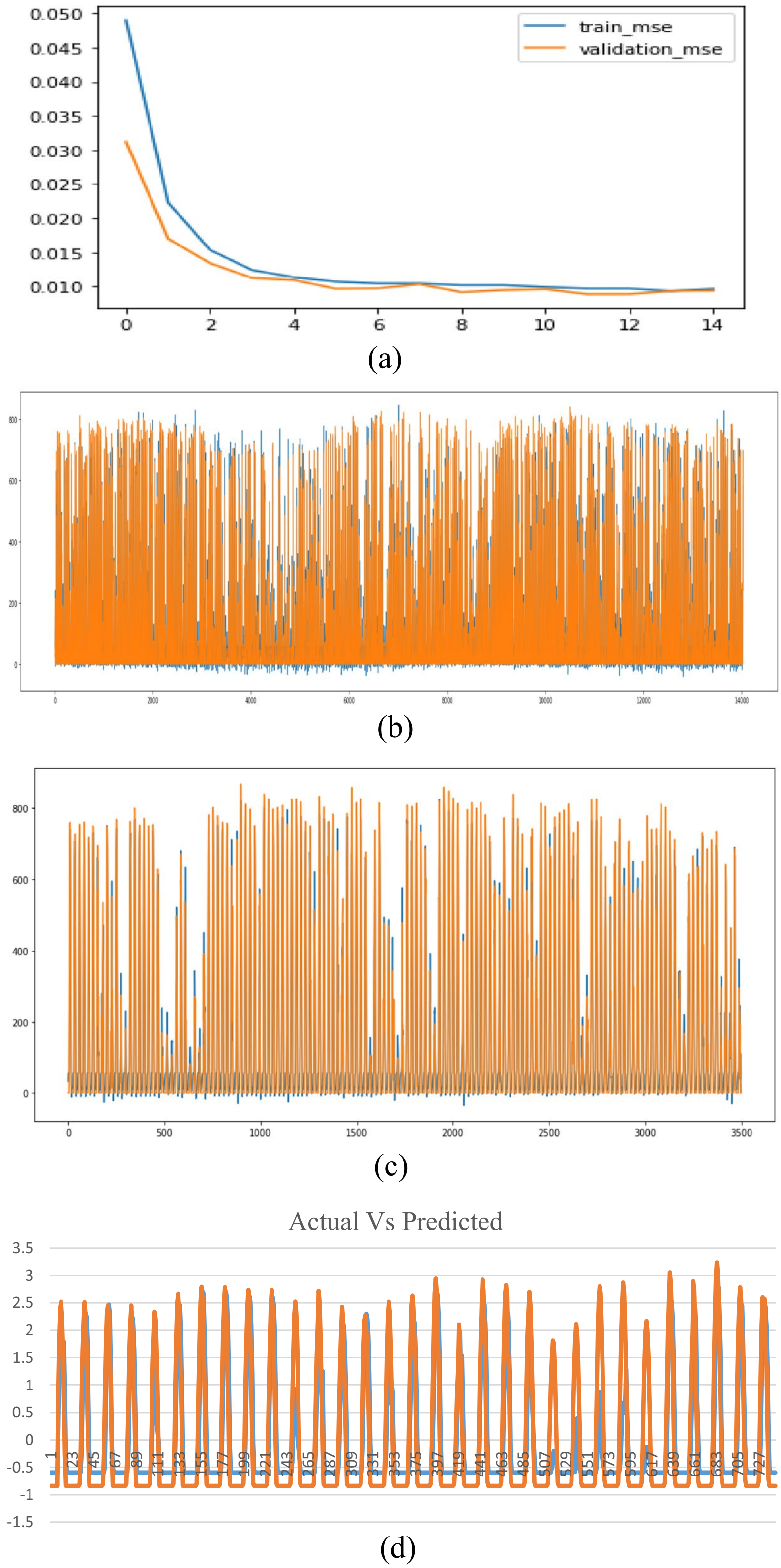


Fig. 9 **a** Training and validation of Ulsan train_mse and validation_mse, **b** Ulsan train prediction (x-axis = no. of observation; y-axis = power), **c** Ulsan test prediction (x-axis = no. of observation; y-axis = power) and **d** Conventional forecasting method showing power output (x-axis = no. of observation; y-axis = power)

MAE = 0.03 while the RMSE = 0.06, this indicates that machine learning is a reliable technique for solar power prediction; see Table 13 for the summary of result for each of the cities.

Solar power generation analysis using awka dataset

Figure 11 shows the result of the predicted energy from Awka region based on neural network trained by data from Ulsan solar generator. Normally, the datasets from

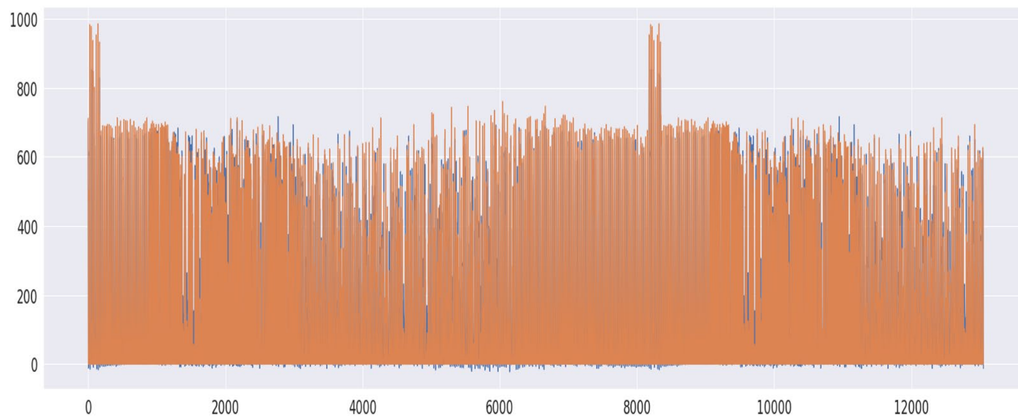


Fig. 10 Actual against predicted power (kW) output of Abakaliki

Table 13 Summary of result

Region	No. of epoch	No. of observation	Energy output (kWh/m^2/day)	MAE	RMSE	R^2	*Global Solar Atlas estimate (kWh/m^2/day)
Abakaliki	30	13,052	4.92	0.03	0.06	0.94	4.87
Awka	30	12,832	4.77	0.04	0.07	0.92	4.72
Enugu	30	12,777	4.98	0.04	0.05	0.93	4.82
Owerri	30	12,817	4.68	0.04	0.06	0.91	4.59
Umuahia	30	12,802	4.61	0.03	0.05	0.93	4.66

* Estimated output of the studied location as shown by Global Solar Atlas—https://globalsolaratlas.info

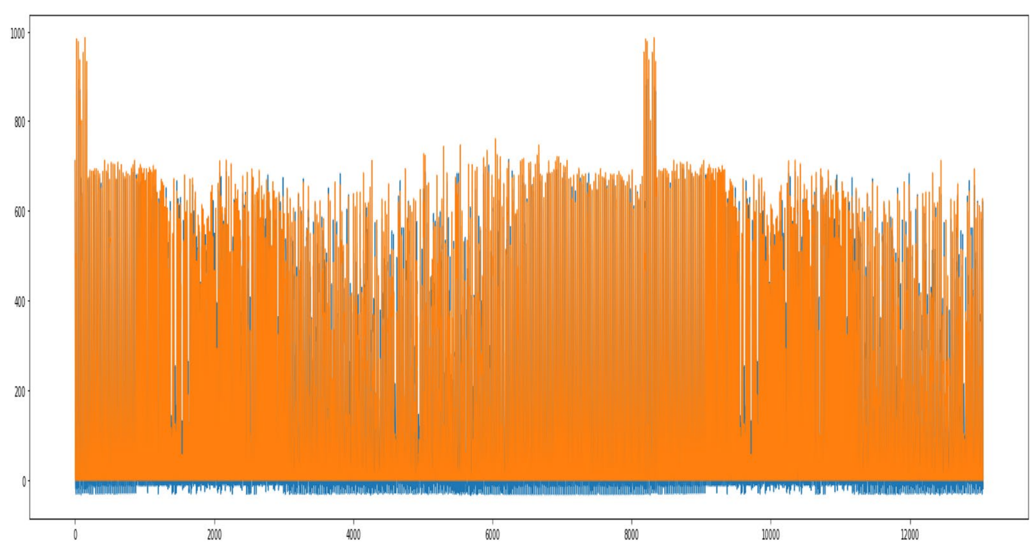


Fig. 11 Actual against predicted power (kW) output of Awka

NASA are analyzed relying on solar radiation data from the target region. Hence, the reason for deep learning technique as stated in section one of this study, is to ascertain the reliability and accuracy of solar energy prediction using machine learning technique. Therefore, as can be seen in Table 13, the accuracy of prediction using machine learning technique is high. This indicates that the technique is very reliable for solar energy prediction. The mean absolute error (MAE) of 0.04 and root mean square error (RMSE) of 0.07 are significantly low, indicating a high accuracy in prediction.

Solar power generation analysis using enugu datasets

Figure 12 represents the result of the predicted energy from Enugu. The idea is to compare the predicted result with the actual so as to ascertain the accuracy of machine learning approach using Ulsan trained dataset as the benchmark for determining the accuracy of machine learning technique for solar power prediction. With a mean absolute error (MAE) of 0.04 and root mean square error (RMSE) of 0.05, it indicates that machine learning is reliable for solar power estimation. The prediction mean absolute error and root mean square error were low, indicating a high accuracy in prediction. Also, the coefficient of determination (R^2) which shows a result of 0.93 is an indication of how well our model predicted the outcome.

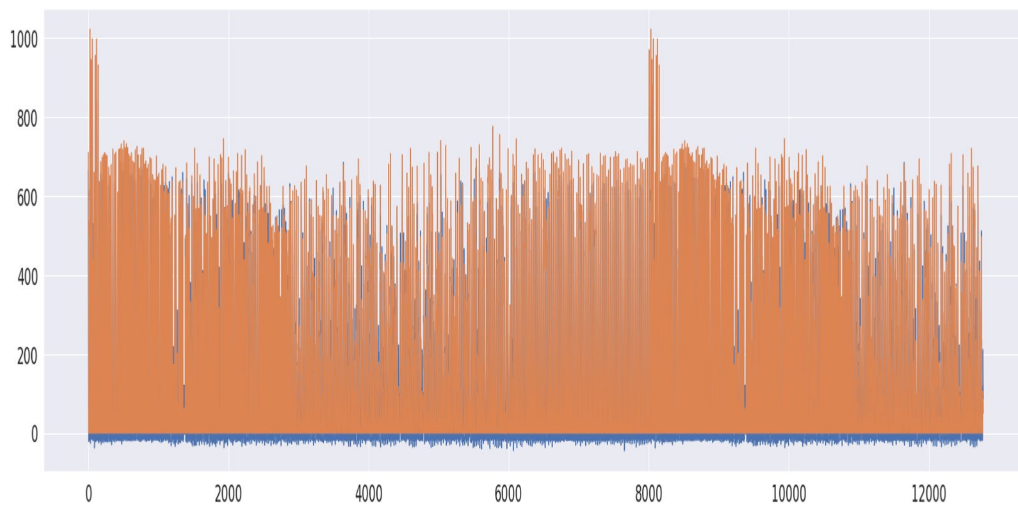


Fig. 12 Actual against predicted power (kW) output of Enugu

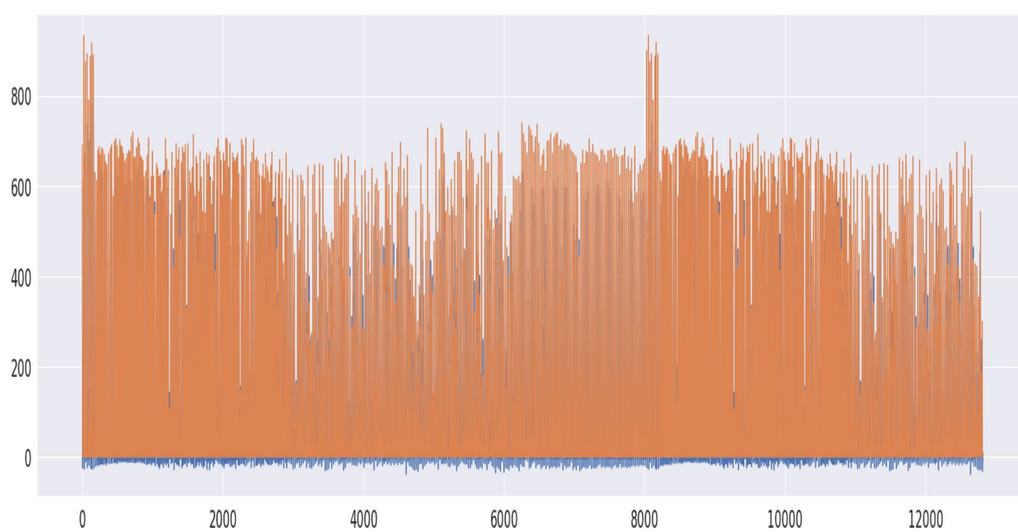


Fig. 13 Actual against predicted power (kW) output of Owerri

From the overall analysis, Enugu region is the region with the highest energy potential.

Solar power generation analysis using owerri dataset

Figure 13 indicates the solar energy prediction for Owerri. The result of the prediction shows that the solar energy potential from the area is relatively lower than most of the other cities. This places the Owerri at a disadvantaged position when compared with the other regions in terms of consideration for solar power investment. However, the investment decisions should not only be based on this, other economic variable such as the city's conducive environment to do business should also be considered. After predicting the energy potentials of the Owerri using machine learning technique, it was discovered that the predicted result is in variance with the estimated energy from NASA database. It can be seen from the Fig. 13 that a significant difference (18.5%) in solar power output (peak) exists between the actual data which was generated from NASA database and that of the predicted result from the neural network trained by the data generated from a solar plant in Ulsan. The mean absolute error (MAE) of 0.04 and root mean squared error (RMSE) of 0.06 from the machine learning prediction were low; indicating a good model performance that could be relied upon for energy prediction by machine learning technique. Table 13 summarizes the prediction error for each region, as well as the energy estimations for the regions. Also, the coefficient of determination which is 0.91 was used to measure how accurately the model performed. It indicates the proportion of variation in the dependent variable that was predicted by the LSTM model.

Solar power generation analysis using umuahia dataset

In Fig. 14, the result of the predicted energy from Umuahia region shows the comparison between the actual data from NASA database and the predicted energy. The result indicates a clear departure from the actual energy data and the predicted energy. Of course, the actual energy data were estimated relying on the solar radiation data of Umuahia region. To ascertain the accuracy of our model, the cities' energy potentials including that of Umuahia, were predicted using

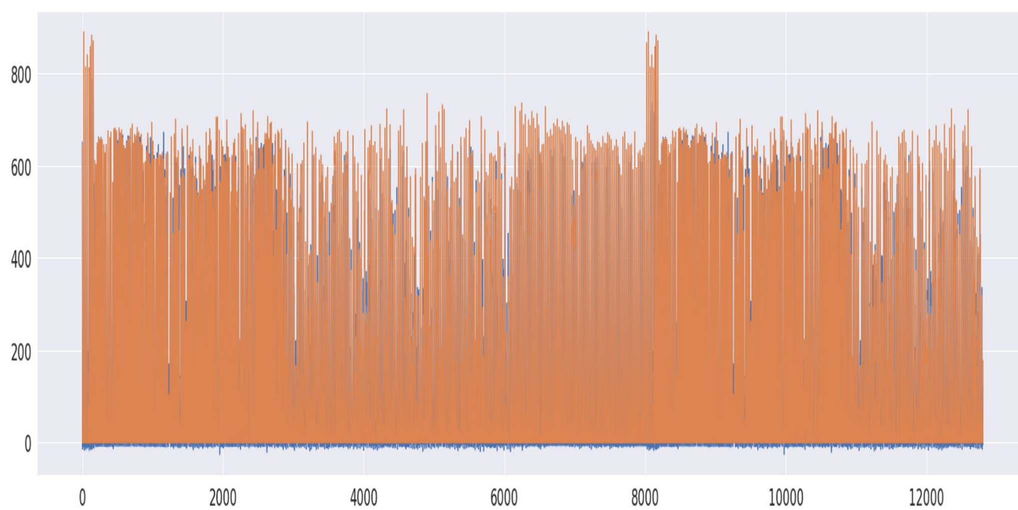


Fig. 14 Actual against predicted power (kW) output of Umuahia

Table 14 Yearly Average Electricity Consumption, 2020 – 2022

Region	Total Consumption (GWh)	Consumption Per Capita (kWh)	Population (in millions)	Population Density (per km2)	Electricity Access by Population (%)
Ebonyi (Abakaliki)	348.15	115	3.42	500	40.0
Anambra (Awka)	683.89	115	5.95	1264	88.1
Enugu (Enugu)	638.56	115	4.40	1300	55.4
Imo (Owerri)	626.63	115	5.22	1063	70.0
Abia (Umuahia)	651.32	115	3.84	863	81.7
National Average	24610	115	210	232	55.4

Source: National Population Commission, National Bureau of Statistics, World Data Info (web) the neural network trained by Ulsan dataset. The mean absolute error of 0.03 and root mean square error of 0.05 indicate a high accuracy in prediction. Umuahia is the region with the lowest energy estimation based on the analysis from the machine learning. However, energy consumption in the region is relatively high (see Table 14). Even though its solar energy potential is the lowest, the energy generation is high enough to generate electricity for both residential and commercial purposes in the region.

Each of the regions under study has an average 4 h of solar radiation per day. The energy estimation for Abakakili = 4.92 kWh/m^2/day; it is the region with the second highest solar PV potential. Although it is a small city with little industrial and commercial activities. As can be seen in Table 14, the average annual consumption for Abakaliki = 27.0 (106 MWh). This figure is twice less than the average consumption for Awka. Awka is one of the three biggest industrial hubs in Nigeria. It has a very densely populated residential and commercial areas, with large industrial activities. The result of the estimated energy generation for the region = 4.77 kWh/ m^2/day (see Table 13). Whereas it is not the region with the highest solar energy potential, it is the region with the largest electricity consumption in all of the measurement strata above—residential, commercial, and industrial consumption. The energy demand in this region is very high, therefore, there is need to first investigate possible energy efficiency and performance improvement with the goal of identifying energy management opportunities that may be adopted to reduce energy consumption (Abolarin et al. 2011, 2013, 2014, 2015) and, thereafter, deploy renewable energy such as solar PV to meet the energy demand of the region.

As can be seen in Table 13, Enugu has the highest amount of solar energy potentials. The analyzed result shows that the region has an average solar energy of 4.98 kWh/m^2/day. This shows a very high potential for a PV system power, and it will be enough to power most home gadgets as well as some simple industrial equipment. Both its residential, industrial, and commercial energy consumption are above the average consumption in the five regions selected for the study. Therefore, considering the solar energy potentials in the area, investment in solar power generation by both private and public institutions will certainly help in cushioning the effect of power cuts and load shedding in the region, as well as help in boosting economic activities.

The regions with the least energy potentials are Owerri and Umuahia region which have 4.68 kWh/m^2/day and 4.61 kWh/m^2/day, respectively. Also, electricity consumption in the regions is relatively lower than those of Awka and Enugu in the case of Owerri region. In consideration of the above, more attention should be given to the region with the highest energy demand—Awka. This is because, it is the region that needs energy the most, for both residential and commercial activities. Since all the regions have a good potential for solar energy generation, efforts should be made in providing more energy to the region with the highest demand, thereafter, investments can also be made in other regions.

In view of the discussion above, it is imperative to state the implication of installing a solar power generating panels in the different region. However, because the major aim of this study is to identify the region with the highest potential, Enugu region shall be our focus. Whereas there a lot of factors that can affect the amount of energy generated by a solar panel, a typical single solar panel within Enugu is expected to generate an average of about 5 kWh/m^2 per day. This could help in saving about $0.23 on electricity costs per day. This amount may seem insignificant, but that is just the energy savings for a single panel on a daily basis. This is in addition to the huge energy demand gap that would be bridged.

In determining how much effect a solar panel installation is expected in Enugu, which is the region with highest energy potential, the unit peak power of a suitable solar panel available in the market and the peak sun hours in the area are considered. Thus, if a home in Enugu installs a 370-Watt solar panel with average 4 sun hours in a day, the solar PV is expected to generate 1,480 Watt-hours of electricity per day. This can be expressed in kilowatt-hours per panel per day as follows:

370 Watts/panel × 4 sun hours = 1480 Watt-hours per day/panel

1480 Watt-hours/1000 = 1.48 kWh per day/panel

This is just a simplified way of determining the amount of energy an average 370-Watt solar panel is expected to generate. However, the actual amount may fluctuate day by day, hour by hour depending on the number of panels required to form an array to meet the maximum daily energy need, the unit peak power of the choice solar PV, panel efficiency and some other factors such as dusts,

Table 15 Estimated generation of a single panel assuming 4 sun hours per day

S/N	Solar panel model	Unit solar PV peak power rating (W)	Calculated energy kWh/day
1	Sun Power A Series	425	1.70
2	LG NeON	405	1.62
3	REC Group Alpha Series	405	1.62
4	Q. Cells & Q. Peak Duo	385	1.54
5	Panasonic EverVolt	380	1.52

area etc. The energy generation capacity will also vary from panel to panel as can be seen in the Table 15.

The share of renewable energy in Nigeria's energy mix is currently about 12% but is projected to reach 20% by 2030. The result of the analysis shown that Enugu region has the highest solar energy potential, probably because of its strategic location on the northern plains of Southeastern Nigeria. However, Awka region was discovered to be the region with the highest energy consumption out of the five (5) regions selected for the study. This is largely due to the high level of industrial and commercial activities in the region. It also has the largest population density per km^2.

Conclusion and recommendation

Conclusion

In this study, analysis of solar energy potentials in Nigeria was conducted using deep learning. Two years weather data from NASA database were collected for the study. The data were analyzed by regions to identify the region with the highest solar energy potential for possible investment in solar power generation. Machine learning was conducted to determine the accuracy of the model for power prediction using Ulsan dataset. After conducting ML for the Ulsan area, the model performance was good; therefore, the neural network was applied to the datasets of the 5 Nigeria regions under study. To know if ML method is better than conventional method of solar power prediction, excel spreadsheet was utilized to analyze the same dataset. It was discovered that ML method is better, because its accuracy was higher than conventional method.

Nigeria has an average solar radiation of about 6.5 h per day. Unfortunately, it has remained untapped and almost totally neglected. Although, solar PV is limited by intermittency of power supply due to weather and climatic conditions, it is possible to get a way around it through the deployment of relevant technology such as artificial intelligence and machine learning for accurate energy demand forecast and power prediction. Also, adequate investment in energy storage system (ESS) is another way to mitigate the intermittency of solar power. Therefore, scientific approaches like this study can help establish guide and requirement for the construction and operation of solar power plants in Nigeria.

As at now, the infrastructural capacity of the Nigerian electricity value chain is inadequate to meet the country's energy demand. Even the available facilities are mostly outdated. Nigeria's electricity generation capacity is put at about 15 GW, while the actual power generation revolves around 3500 and 5000 MW for a country of over 200 million people. This is quite a poor performance when compared to other countries even within the African continent. For instance, South Africa, a country with 50 million population has an installed generation capacity of up to 46 GW. South Africa's capacity is three times that of Nigeria's, while Nigeria's population is four times that of South Africa. This is indeed an irony. This has caused an increased number in power cuts and load shedding. It has also affected the economy tremendously in all facets, including industry, manufacturing, transportation, construction and general services.

The major hiccups to the accelerated development of technology to exploit, explore, and harness renewable energy in Nigeria are unstimulated demand, non-implementation of the available regulatory and institutional framework, as well as lack of incentives for private investors. Nigeria's annual consumption of electricity has been steadily growing. Making it even increasingly important to urgently expand energy supply through a robust investment planning. Energy consumption has increased from 1273 GWh in 1970 to 29,573 GWh in 2019 (Abolarin et al. 2014). This, however, represents a repressed demand caused by inaccessibility to the national grid and insufficiencies of electricity supply (Abolarin et al. 2013).

Recommendation

Based on the result from the study, appropriate recommendations were made considering the aforementioned indices on the most suitable region(s) for solar power generation. It is expected that the result of this study will assist the government in taking appropriate actions in line with the country's renewable energy policy guideline.

The recommendations made were as follows:

- Domestication of renewable energy policy should be a matter of urgency and deliberate policy. This policy will make renewable energy not only available but affordable to both urban and rural areas. The main regulation guiding renewable energy in Nigeria is the Electricity Act of 2023 which was recently passed by the immediate past government. Although the Act has been passed, it is yet to be domesticated across the 36 states of the federation. Domestication of the policy will go a long way in ensuring the availability and affordability of renewables in the country.
- States and regions should be encouraged to harness their energy potentials so as to adequately generate and transmit energy in their various regions. This is a very important aspect of the new Electricity Act 2023 which provides for individual states/regions to explore and harness its own energy resources for electricity generation for citizens of the state. Every region in Nigeria has one form of renewable energy resources in abundance. However, prior to the signing of the Electricity Bill 2023 into law, Nigeria's elec-

tricity generation and transmission was in exclusive list; this means that only the national government has the power to generate and transmit electricity. But now, states and regions can equally generate and transmit electricity.
- Government should encourage massive investment in renewable energy by private investors to create a viable alternative to the traditional sources of energy. The Nigeria's renewable energy market remains grossly untapped, partly due to lack of enabling laws and conducive environment for business. This has negatively impacted the exploration and integration of renewables into the energy mix. With the passing of the Electricity Act 2023, it is envisaged that massive investment will be made by both the private and public sectors to bolster the renewable energy market, and more especially solar energy.
- Government should fast-track the domestication of enabling laws and policies to drive energy transition at both rural and urban areas. Nigeria's climate action ambition is to achieve carbon neutrality by 2060. Undoubtedly, this climate ambition can be fast-tract to ensure that the government achieves it by the year 2060 or even earlier. Given that Nigeria's northern region is threatened by desertification, the central region by flooding, and the southern region by pollution, erosion, and associated socio-economic challenges, all allude to the reality and debilitating impacts of climate change. Consequently, the need for an urgent accelerated action to limit the impacts of climate change can never be over-emphasized.

Finally, this research work was constrained by time and resources. It was not easy having regular job schedule and carrying out research at the same time. Also poor internet connection and epileptic power supply was a great limitation to this project. And this is indeed, one of the motivations for carrying out this research—solving Nigeria's energy demand problems. In view of the foregoing, there is need for more work to be done in the future on bridging the energy demand gaps in Nigeria using renewable energy technology.

Abbreviations

ANN	Artificial Neural Network
CNN	Convolutional Neural Network
ECN	Energy Commission of Nigeria
EIA	Energy Information Administration
GDP	Gross Domestic Product
LSTM	Long–Short Term Memory
MAE	Mean Absolute Error
MSE	Mean Square Error
NASA	National Aeronautics and Space Administration
NREL	National Renewable Energy Laboratory
PV	Photovoltaic
PPA	Power Purchase Agreement
RMSE	Root Mean Square Error
TCN	Transmission Company of Nigeria

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Author contributions
SI: Contributed to conceptualization, methodology, data curation, software development, formal analysis, investigation, visualization, and wrote the original draft, KS: Supervised, provided conceptualization, methodology, resources, validation, and participated in reviewing and editing, TOS: Provided validation and contributed to reviewing and editing, DRE: Participated in reviewing and editing, SMA: Provided resources, validation, and contributed to reviewing and editing, AAF: Handled data curation, validation, and contributed to reviewing and editing. All authors made significant contributions in analyzing and interpreting the output (energy) data, as well as writing the manuscript. All authors also read and approved the final manuscript.

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Availability of data and materials
The datasets used for analysis in this study are available from the corresponding author upon request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
We declare that we have no known competing financial interests or personal relationships that could have influenced the results reported in this paper.

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