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OPTIMAL SIZING OF HYBRID MICRO GRIDS USING GENETIC ALGORITHM

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Abstract – **This project presents a technique for optimal sizing of hybrid microgrid. To achieve a certain load demand for microgrid system. Hybrid microgrid is made of a Solar photovoltaic system, Wind turbine system and energy storage system. Hybrid microgrids based on renewable energy resources is cost effective. Efficiency and performance will increase. Hybrid microgrid comprise of several parallel connected distributed resources with electronically controlled strategies, which are capable to operate in both islanded and grid connected mode. System reliability and cost effectiveness are major factors considered for designing hybrid microgrid to achieve better power management scheme. Genetic Algorithm scheme is applied to identify the sizing of wind turbines, solar, energy storage system and find the optimal configuration of hybrid microgrid system. The design and optimal operation of hybrid microgrid system has been developed and validated through MATLAB software. The reliability of the microgrid system is modeled based on the Loss of power supply probability. For optimization, genetic algorithm is used to minimize the total cost of the system satisfying some reliability and operation constraints.**

Keywords: Hybrid Microgrid, Renewable Energy, Battery, Solar Photovoltaic, Wind, Battery, Genetic Algorithm (GA)

1.Introduction

Providing access to reliable, affordable energy, and clean energy by adopting microgrid system is important for countries looking to achieve their sustainable development goals as the extension of the grid is capital and time expensive. These microgrids are small electrical power systems that connect several electricity users to some distributed power generators and energy storage systems, which are mainly interconnected by power converters and can be made of renewable energy sources or hybridized with fossil fuel generators. Hybrid solar system, wind turbine, and energy storage system are used for grid electrification applications, and they are good for applications in hot climates. However, due to the CO_2 emission, delivery cost and rising price of diesel fuel, renewable energy sources are more and more popular in microgrid development, especially in remote areas. Both wind and solar power sources are intermittent as they depend on weather and climate changes; however, hybridizing the two sources can overcome this drawback . Furthermore, using a hybrid energy storage system in microgrid system can increase the system stability. The solar is used as the main power supply in the system.The wind turbine is used as complementary power supply to support the load when the solar production is low (e.g., cloudy day) or not available (night times). Additionally, the energy storage system is used as a back-up power to support the load when the power generated by the solar and wind turbine cannot handle the load demand. However, improper sizing of the system components may result in higher microgrid cost and low reliability. For example, an oversized solar array may increase the microgrid investment cost and decrease its stability due to the unpredictable nature of solar power generation. Similarly, too much energy storage system capacity increases the cost and notenough energy storage system capacity may result in low system reliability. Consequently, many optimization problems are based mainly on either cost reduction or required re-liability of the microgrid power system

Previous studies have investigated various methods of optimally sizing in different scenarios of hybrid microgrid applications, presented a simple sizing algorithm to obtain the number of solar and wind turbine units along with the storage capacity for a stand-alone hybrid microgrid. The work presented a simple method to optimize the size of solar, wind turbine and energy storage system using an iterative method driven by the loss of power supply probability to minimize the 20-year total cost including capital, operation, and maintenance cost of the microgrid. Other research studies focused on the operation optimization of microgrids.

This paper aims to find the optimal size of solar PV array, wind turbine and energy storage system for a micro grid by using genetic algorithm, to minimize the total cost of the microgrid (which includes the capital and operating costs), while always satisfying the load demand with a desired reliability. Figure shows the architecture of a typical hybrid solar, wind, and energy storage system of microgrid. In the figure is a DC-coupled microgrid in which the solar panel and the energy storage system are linked via a

DC/DC charge controller, creating a DC bus that carries the power from the wind turbine via a rectifier and power the household load using an inverter. The DC-coupled microgrid uses less power conversions (resulting in a small efficiency gain) com- pared to an AC-coupled microgrid .

The reliability of the microgrid system is modeled based on the loss of power supply probability. For optimization, a Genetic Algorithm is used to minimize the total cost of the system over a 20-year period, while satisfying some reliability and operation constraints. A case study addressing optimal sizing of hybrid microgrid in Nigeria is discussed.

2.Modelling

PV model

As the main power supply in this off-grid solar hybrid MG system, the output power of a PV module is estimated from (1) based on the solar irradiation at time *t,* and the efficiency of the PV module is given by (2).

$$P_{PV}(t) = \eta_{PV} \cdot A_{PV} \cdot G(t) \qquad (1)$$

$$\eta_{PV} = \eta_{STC} \cdot \eta_{MPPT}[1-\alpha(T_C - T_{STC})] \qquad (2)$$

Where,

A_{PV} is the area of a PV module in (m^2),

G(t) is the hourly total solar irradiance in (W/m^2)

η_{PV} is the efficiency of the PV array,

η_{STC} is reference efficiency of maximum peak power tracker,

Tc is the temperature of PV cell,

T_{STC} is the reference temperature of PV cell,

The temperature coefficient is given by the PV cell manufacturer and can be obtained from the PV panel datasheet. The cell temperature can be obtained from Equation (3).

$$T_c = T_a + \frac{NOCT-20}{800} . G(t) \qquad (3)$$

Where,

T_a is the ambient temperature

NOCT is the nominal operating cell temperature

Wind Turbine Model

The output power from a wind turbine at time t depends on the wind speed and can be obtained from (4).

$$P_{WT}(t) = \begin{cases} 0 & V(t) < V_{ci} \\ a.V^3(t) - b.P^r_{WT} & V_{ci} \le V(t) < V_r \end{cases} \qquad (4)$$

P^r_{WT} $\qquad V_r \leq V(t) < V_{co}$

0 $\qquad V(t) \geq V_{co}$

Where ,

$$a=\frac{PrWT}{(V3r-V3ci)}; \qquad b=\frac{V3ci}{Vr3-V3ci};$$

V(t) is the wind speed at time t in (m/s);

P^r_{WT} is the rated power of the WT in (W);

V_r is the rated speed in (m/s);

V_d is the cut-in speed in (m/s);

V_{co} is the cut-out speed of the WT in (m/s).

ESS Model

Depending on its state of charge, the energy storage system can supply the load when there is lack of electricity (discharge) and store surplus power when the generated power exceeds the load demand (charge). The discharging and charging energies of the energy storage system at time t can be obtained from (5) and (6), respectively

$$E^d_{ESS}(t) = E_{ESS}(t-1) - [E_{load}(t) - E_{PV}(t) - E_{WT}(t)] / \eta d \qquad (5)$$

$$E^c_{ESS}(t) = E_{ESS}(t-1) + [E_{PV}(t) + E_{WT}(t) - E_{load}(t)].\eta c \qquad (6)$$

Where,

$E_{ESS}(t-1)$ is the energy at time t-1 in (kWh);

E_{PV},E_{WT},E_{LOAD} are the PV energy, WT energy and load energies;

ηd and ηc are the discharge and charge efficiencies of the energy storage system.

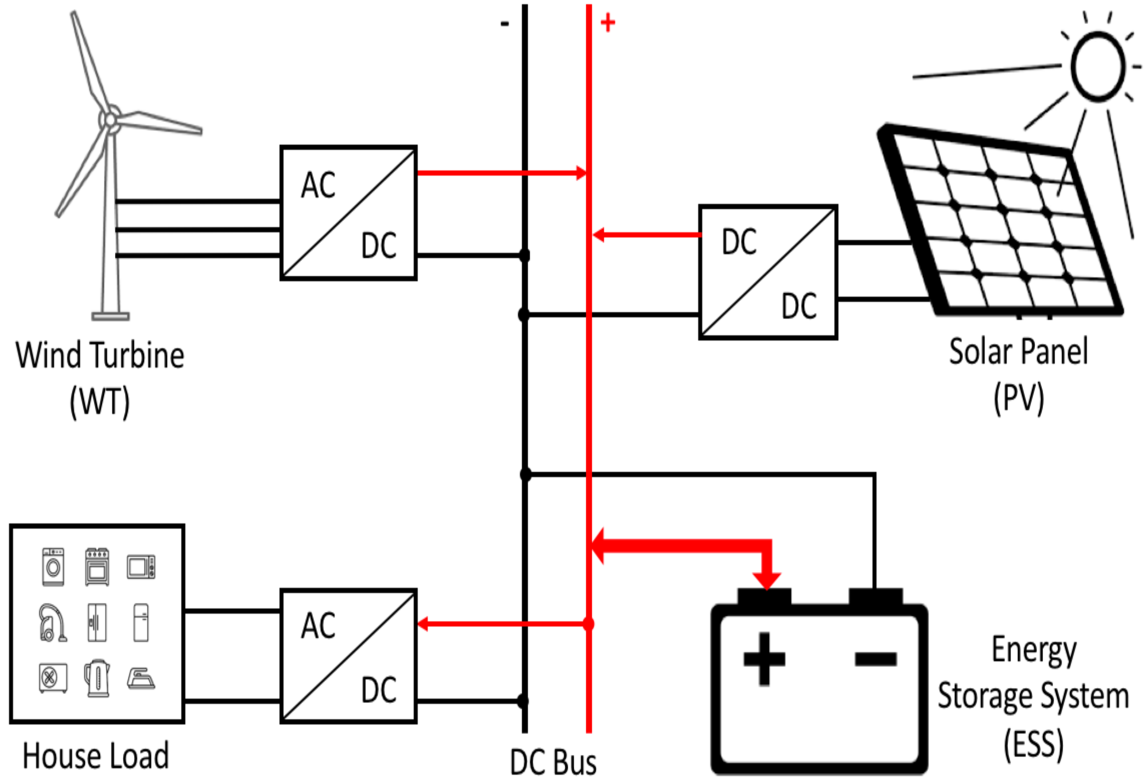


Figure Hybrid microgrid system modelling

Load Profile

The load profile determines the requirements of power supply from the hybrid MG power system. The load profile is modeled according to the dynamic load power demands Load P at times t . In off-grid power system design, the load profile is the driver. Figure shows an example of a per-hour daily residential load demand profile for a group of some households. This double-bell curve, with high demands early in the morning and late in the evening, could be explained as follows:

- Most residents wake up in the morning to prepare for work and school (i.e.
- taking hot showers, preparing breakfast, etc.).
- People then leave for work and school typically from hours 7 to 18 on weekdays.
- Most household members are cooking/warming food, eating dinner, watching
- TV from hours 18 to 22 then go to bed.

The curve shown here in Figure represents a weekend profile as people
wake up later compared to week days and use more power during the day from staying at home

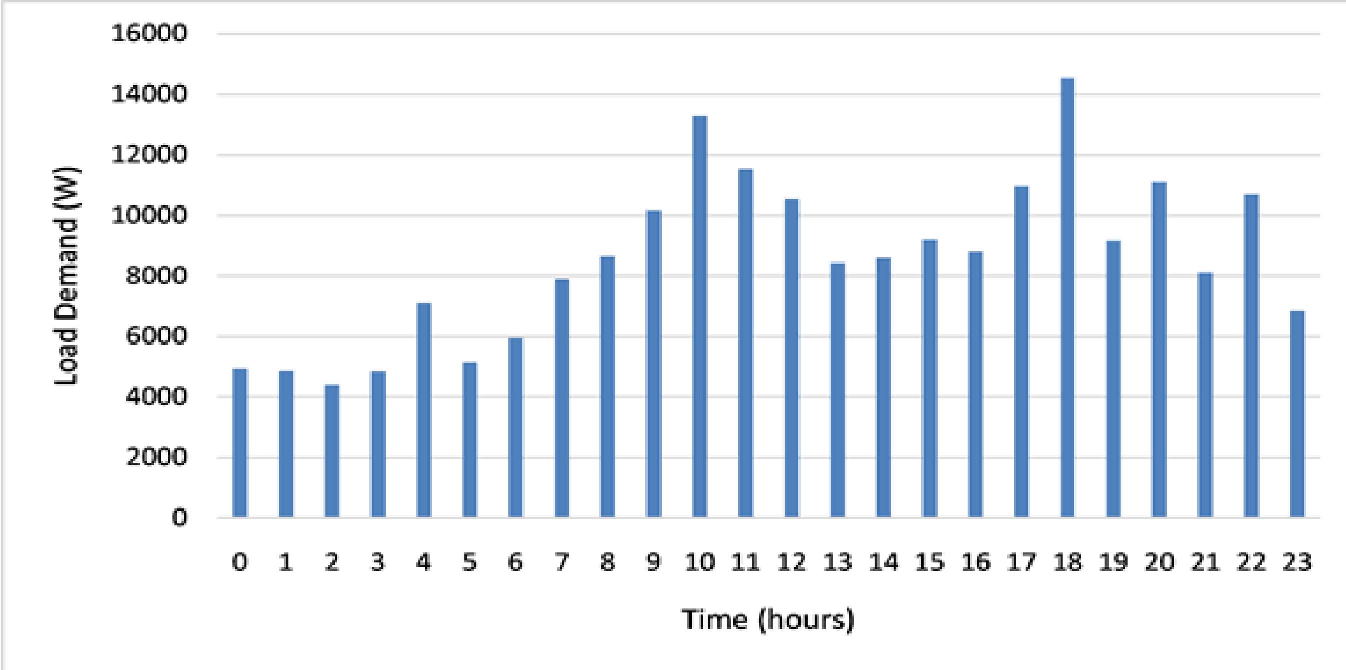


Figure Load profile

Reliability Model

The power balance of the system is illustrated in Figure. When the load demand exceeds the energy generated by solar and wind turbine plus the energy stored in the energy storage system for hour t, this put the microgrid in a Loss of Power Supply

(Psupplied (t) < Pneeded (t)), which is expressed as

$$LPS(t)=P_{load}(t)-[P_{PV}(t)+P_{WT}(t)+P^{d}_{ESS}(t)].\ \eta_{inv}$$

The Loss of Power Supply Probability, which is the reliability index of a microgrid system, for a given time period T can be defined as the ratio of all LPS(t) values for that period to the sum of the load demands.

Objective Function

The objective of this optimization problem is to minimize the capital and operating costs of the off-grid hybrid microgrid over a total life period of 20 years, while satisfying some reliability, operational and stability constraints. This optimization problem is expressed as.

$$\min f\,(N_{PV}, N_{WT}, ESS) = C_{PV}.N_{PV}+C_{WT}.N_{WT}+C_{ESS}.E_{ESS}$$

Where

N_{PV} is the number of PV panels;

N_{WT} is the number of wind turbines;

E_{ESS} is the storage capacity of ESS;

C_{PV} and C_{WT} are total cost of PV and WT;

C_{ESS} is the per unit cost of ESS

Constraints

Reliabilty:

$$LPSP \leq LPSP_{set}$$

PV power limit:

$$P_{PVmin} \leq P_{PV}(t)P_{PVmax}; NPV=0,1,2,3,\ldots..$$

WT power limit:

$$P_{WTmin} \leq P_{WT}(t) \leq P_{WTmax} ; NWT=0,1,2,3,\ldots..$$

ESS power limit:

$$E_{ESSmin} \leq E_{ESS}(t) \leq E_{ESSmax}$$

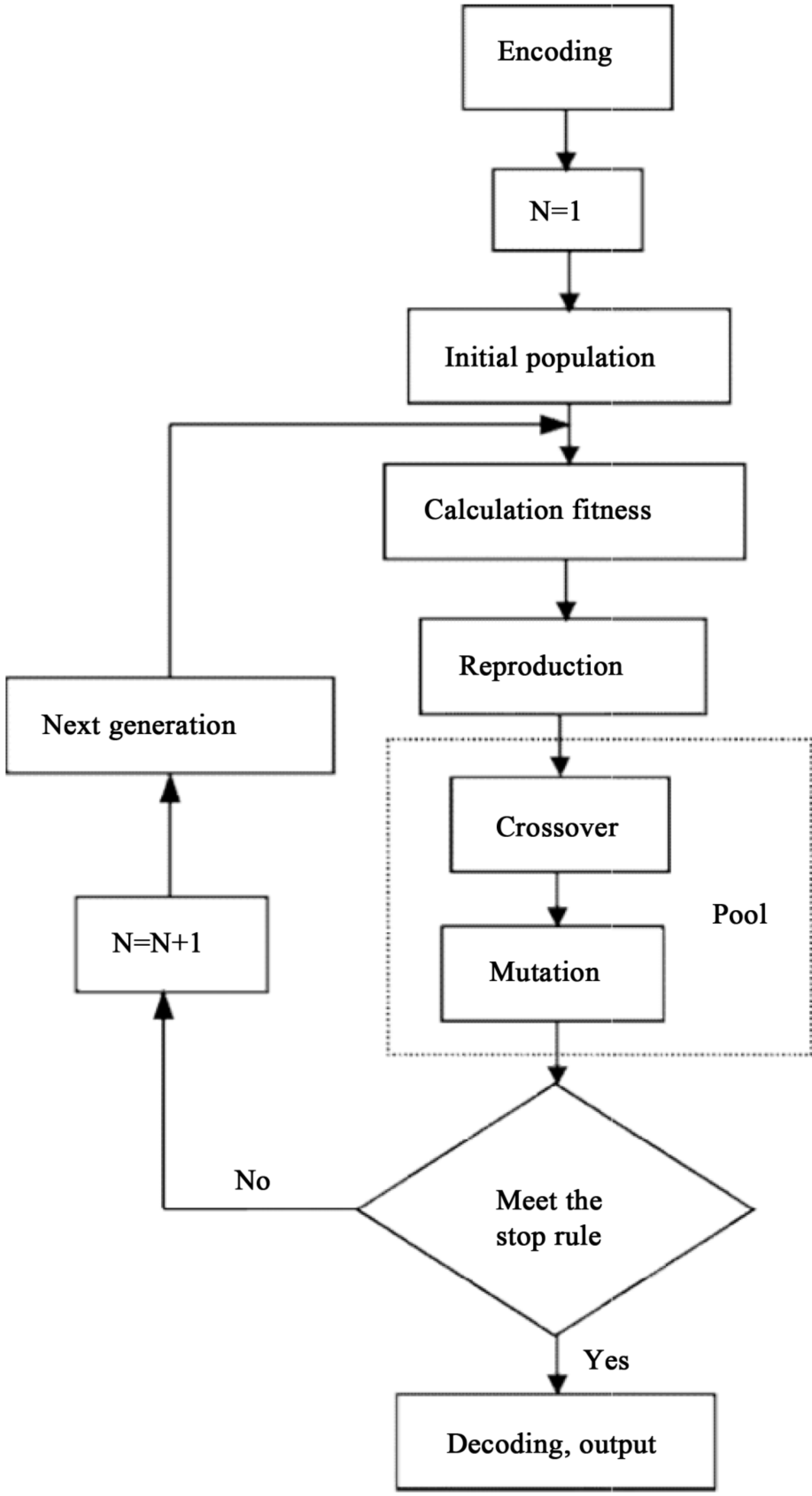
$$E_{ESSmin} = (1\text{-Depth of discharge}).E_{ESSmax}$$

3. Genetic Algorithm

In the past few decades, various nature-inspired computational methods have been developed to solve complex engineering problems One such computational method is Evolutionary algorithms which are generic, optimization algorithms that are biology-inspired mechanisms. Genetic algorithm (GA) is a rapidly growing area of Artificial Intelligence. It is an intelligent method for solving combinatorial, hard optimization problems in n-dimensions. The flowchart of a genetic algorithm is shown in figure. The work in proposed five enhancements were introduced (multiple weighted roulettes, multiple cross over points, multiple mates, utilizing the Daubechies wavelets (D4) and using normal distribution for selecting the initial population). The convergence velocity of the algorithm is also improved thereby reducing the time taken for the algorithm to reach the sought solution. A basic part of the selection process is to stochastically select from one generation to another to create the basis of the next generation. The under- lining requirement is that the set of fittest individuals would have a greater chance of survival than the set of weaker ones. This inheritance nature in those fitter individuals will tend to have a better probability of survival and will go on forward to form updated mating pool for the next generation. Weaker individuals are not left without a chance though. In nature those individuals may have genetic coding that may also prove useful to future generations.

Selection is the first genetic operation in the reproductive phase of genetic algorithm. It helps the genetic algorithm by directing the genetic search towards promising regions in the search space Selection pressure is a crucial factor that determines the efficiency of the algorithm and is reduced in our proposed algorithm. The first enhancement proposed is to use multiple weighted roulettes, each designed to complement the others. This will further distribute the selection pressure for one generation to another. The job that GAs have in this case is to mate sets of individuals and then replicate this selection process. The usual implementation is by crossover. The only general requirement is that the offspring carry forward the important genetic material from the parents, whilst introducing enough variation that they survive. The crossover method emulates this process by exchanging chromosome patterns between individuals to create offspring for the next generation.

The second and third enhancements are to use multiple cross over points as well as using multiple mates as a function of results of mating individual parents creating some offspring. Those offspring will have of the genetic material of both parents. There are three options regarding the fitness of the offspring, they can be weaker, the same or fitter than their parents. If they are weaker, they will tend to die out—if they are stronger their chances of survival are better. It is of general note that the stronger the parents are in



terms of fitness then the fitter the offspring will be. The variation caused by this process allows the offspring to search out different available niches,*i.e.* find better fitness values and subsequently better solutions.

The fourth enhancement proposed is to utilize the Daubechies wavelet (D4), which is named after its discoverer the mathematician Ingrid Daubechies, as a preprocessing step. The D4 transform has four scaling function coefficients and can be extended to multiple levels as many times as the signal length can be divided by 2. D4 was compared to other wavelets. The HAAR wavelet for instance is simple, memory efficient and computationally cheap. It uses two scaling and wavelet function coefficients, thus calculates pair wise averages and differences. Daubechies wavelet family is the most popular wavelet family used for texture feature analysis, due to orthogonal and compact support abilities. Daubechies averages over more pixels, it is smoother than the HAAR wavelet. It is Similar to the well-known Fourier transform, but it takes care of rapid transitions better than Fourier.

The fifth enhancement is used for initializing the initial population and it is done by replacing the uniform distribution with the normal distribution. The normal (Gaussian) distribution is the most widely known and used of all distributions. Because the normal distribution approximates many natural phenome- na so well, it has developed into a standard of reference for many probability problems. That is why it was selected to be the fifth enhancement proposed todeal with the step of selecting the initial population. Some of the characteristicsof the normal distribution are that it is symmetric, bell shaped and continuous for all values of X between -∞ and ∞ so that each conceivable interval of real numbers has a probability other than zero. Normal distribution is actually a family of distributions since the two parameters μ and σ determine the shape of the distribution.

4.Case Study

The location of Guzape (suburb of Abuja), Nigeria (Latitude 9˚0'31"N, Longitude 7˚30'50"E) is used as site for the case study. The global horizontal solar irradiance, ambient temperature and wind speed data were taken from the NREL data sets and used to calculate the output powers of the solar and wind turbine. contains information about the solar, wind turbine and energy storage system parameters used in this paper. The site consists of 10 apartments with some outside lighting.

5.Results and Discussion

It was found that the optimal size of the site is 168 solar panels, 5 wind turbines with 200 kWh of energy storage for the minimum total 20-year cost of 1,91,19,006 for 80% of depth of discharge based on the desired operation and reliability constraints with low power supply probability. Figure shows an aerial view of the project site in Nigeria.

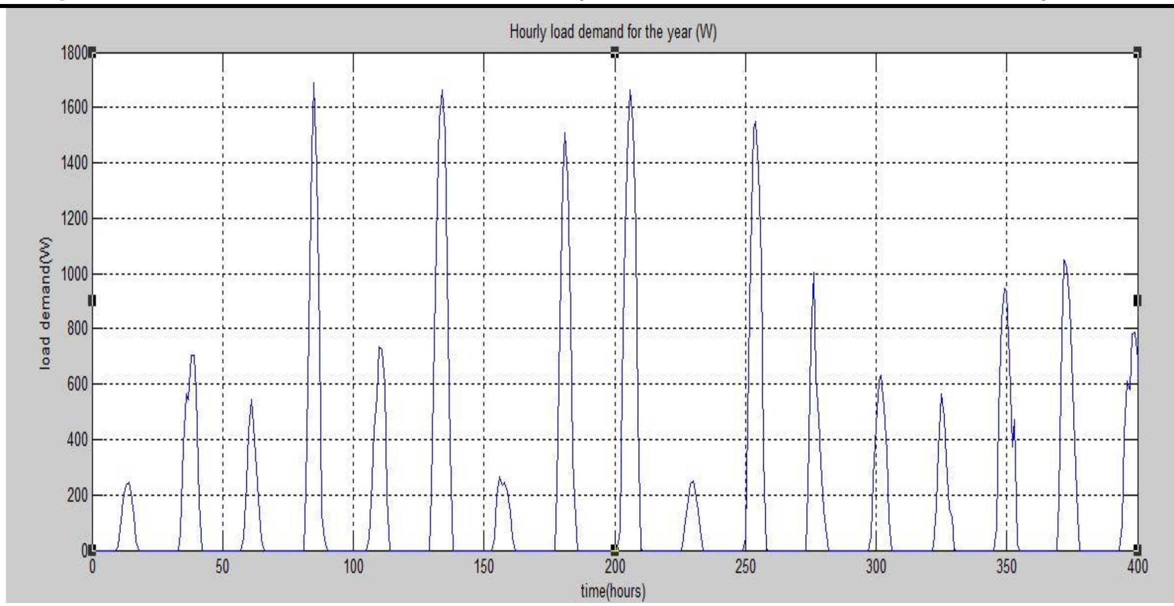


Figure Hourly Load demand

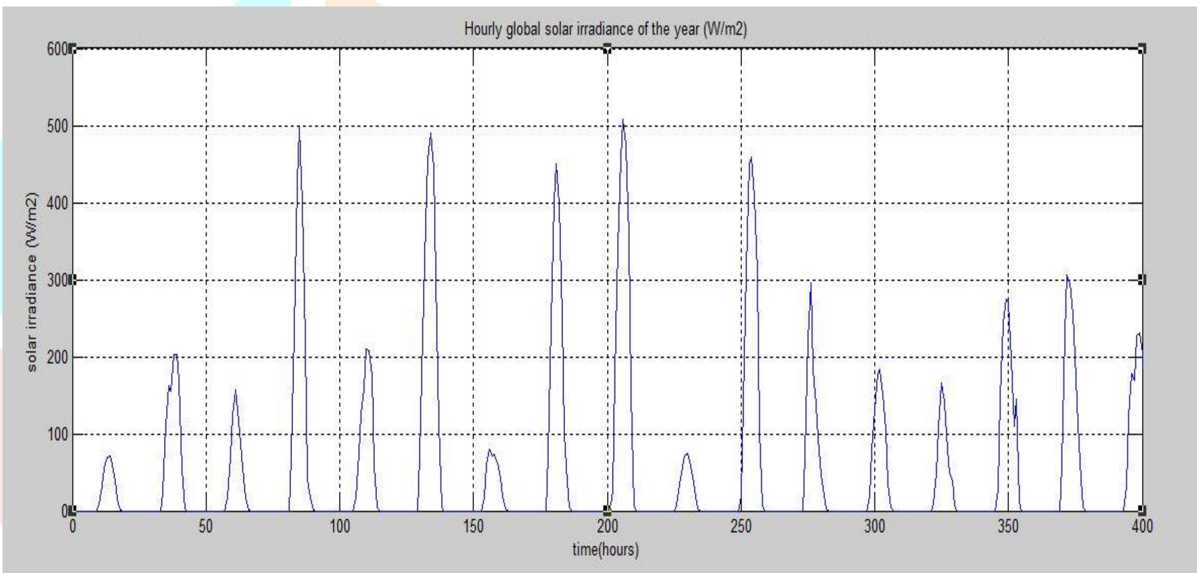


Figure Hourly Solar Irradiance

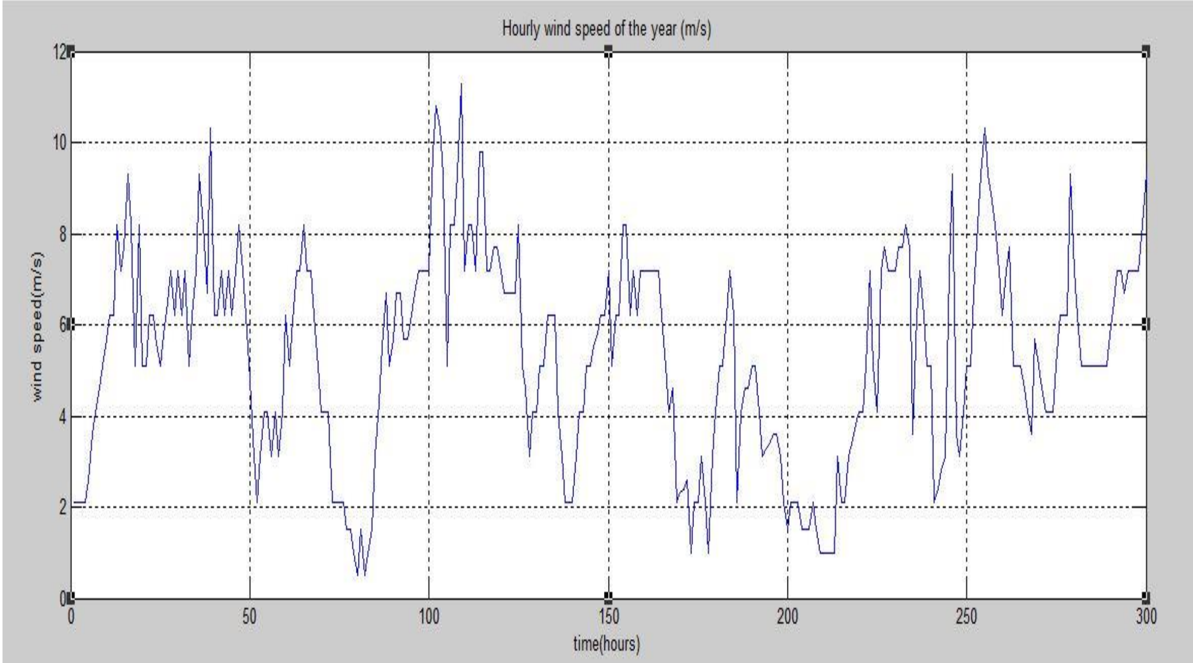


Figure Hourly Wind Speed

Figure Aerial view of location

The genetic algorithm used to minimize the total microgrid cost, while considering different low power supply probability values for system reliability. The results for 80%, 70%, 60% depth of discharge were presented in table.

Depth of discharge 80% :-

	Genetic Algorithm
No. of solar panels	164
No. of wind turbines	5
Solar power	41kW
Wind power	7kW
ESS	200kWh

Depth of discharge 70% :-

	Genetic Algorithm
No. of solar panels	166
No. of wind turbines	5
Solar power	42kW
Wind power	7kW
ESS	200kWh
Total Cost	1,92,25,119 INR

Depth of discharge 60% :-

	Genetic Algorithm
No. of solar panels	168
No. of wind turbines	5

Solar power	42.8 kW
Wind power	7 kW
ESS	200 kWh
Total Cost	1,93,18,392 INR

6.CONCLUSION

A sizing of solar PV, wind turbine, and energy storage system hybrid microgrid using a Genetic Algorithm is proposed. A case study involving the optimal sizing of hybrid microgrid system site in Nigeria using real field data was discussed. For the case study, a special MATLAB program was developed along with the genetic algorithm to obtain the optimal size of the micro grid. That is the combination of solar, wind turbine and energy storage system that met the load demand subject to the operation constraints and the desired low power supply probability with the minimum total microgrid cost over a period of 20 years. GA is well suited for optimal microgrid system sizing, and the proposed method is feasible for sizing solar and wind turbine and energy storage system of hybrid microgrid systems.

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