Optimal Sizing of Hybrid Energy Systems in a Microgrid: A Review

S.N Okhuegbe, C.Mwaniki, M.F Akorede

***Abstract*—**With the ever-growing energy demand and coupled with the issues of reliability. Microgrids powered by distributed conventional and renewable energy sources can be utilized to address this problem. Hybrid energy sources offers better reliability and cost effectiveness than a single energy source. Determining the right size of Hybrid Energy Systems is of great importance in order to avoid over-sizing or under-sizing which could greatly affect the cost and reliability of the system. Optimal sizing becomes highly complex when considering multiple hybrid mix and also considering various objectives such as cost, emission, reliability etc. This paper aims at critically evaluating the various cost objectives, reliability indices, mathematical models, and optimization techniques used in optimal sizing of various of hybrid energy mix. It has been found that meta-heuristic techniques are well suited for optimal sizing with Genetic Algorithm and Particle Swarm Optimization techniques being the most commonly used Algorithms. Also, the Hybrid Optimization for Multiple Energy Resources (HOMER) stands out as the widely accepted and used optimization software tool.

***Keywords*—**Distributed Generation, Hybrid Energy Systems, Microgrids, Optimization, Renewable Energy.

1. INTRODUCTION

Electric Power is one important basic amenity needed in our day to day activities, and has been described as the lifeblood of all modern societies[1], with the recent increase in population, technology, urbanization and industrialization, the world energy demand is estimated to increase up to 53% by 2035[2]. This creates a challenge on how to efficiently meet this energy need. Apart from the insufficient supply to meet the growing energy demand, the electric power system in most developing African countries are plagued by poor power reliability leading to regular power outages, load shedding and ageing equipment in the network. In a bid to improve the power situation, various researchers have proposed the use of distributed generation coupled with various renewable energy sources to form a microgrid as a viable option[3], as opposed to the use of conventional large-scale centralized power generation. An incentive of renewable energy is that they are eco-friendly with little to zero greenhouse gas and CO2 emission. One problem with the use of renewable energy such as wind, solar etc., is that they are stochastic and intermittent in nature.

And the usage of an individual renewable energy source cannot guarantee continuous supply of power. One way to better utilize renewable energy sources considering their intermittency is through hybridization, which means the combination two or more renewable/non-renewable energy sources [4]. Hybrid Energy System (HES) consist of a combination of various energy sources, and determining the right size of each of the energy combination is of great importance, as over-sizing could lead to unnecessary increase in cost, and under-sizing could lead to poor reliability and availability of power. So therefore, determining the optimal size of an hybrid energy system creates an optimization problem which increases in complexity as the number of energy source and constraints increase. From Fig 1, we can see that Hybrid Energy Systems are characterized into Stand Alone (Islanded, off-grid) Hybrid Energy System (HES) or Grid Connected Hybrid Energy System (HES)[4]. Grid connected Hybrid Energy Systems can be further characterized to consist of grid systems with storage and grid connected energy systems without storage.

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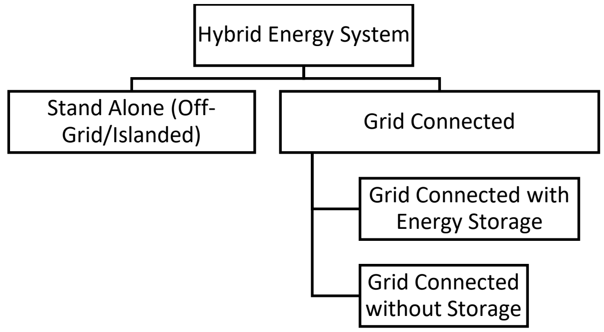

Fig.1 Block Diagram showing the breakdown of Hybrid Energy Systems

The basic schematic and components of a Hybrid Energy Systems consists of renewable/non-renewable energy sources, converters, storage and load.

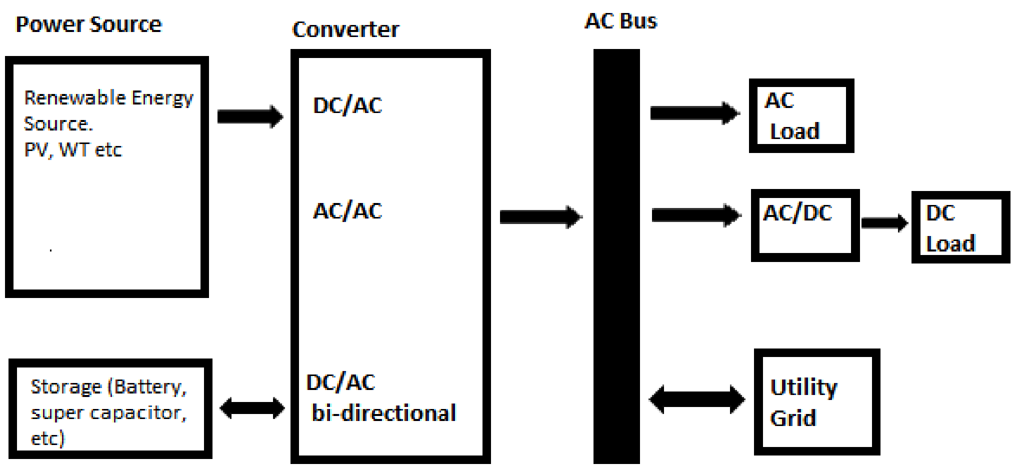

Fig 2. Block Diagram showing schematic of Hybrid Energy Systems in a Microgrid

Fig.2 shows a possible hybrid energy system configuration with various components and load types with an option for grid connection. From the literatures surveyed, the most common Hybrid renewable energy system has been the solar-wind hybrid energy system. The procedure for optimal sizing involves gathering weather data, mathematical modelling of the energy output and finally the application of an optimization technique to optimally size. As, shown in fig.3, in order to effectively size a hybrid energy system, three important data set are required which are mainly;

1. Meteorological Date Set
2. Load Demand
3. System Specification Data

This paper presents a review on the various techniques for optimal sizing of hybrid energy systems in a microgrid, while discussing the various data required, mathematical models and reliability considerations.

II. Meteorological Year Data

The first step to sizing, is the gathering of a Typical Meteorological Year's (TMY) data. Which in essence is the hourly time series weather (solar irradiation, temperature and wind) data for a year (12 months). This leads to 8760 data points. The common weather data are the solar irradiation and wind speed data. The best way to determine the hourly solar irradiation and wind speed is by physically measuring the irradiation and wind speed at the select location. But unfortunately, this process is quite tedious and expensive, in order to circumvent this, there exist various meteorological databases that provide averaged monthly solar irradiation, wind speed and temperature data for various locations across the world. The most common of such database is the Power Access Data Viewer by the National Aeronautics and Space Administration (NASA)which provides a 22 year monthly averaged solar irradiation data[5].The Power Access Data viewer provides afreeuser-friendly interface for researchers to access the meteorological data set for virtually any location. Some other meteorological database include PV-GIS [6], Solar GIS[7], Helioclim1 [8], Helioclim3 [9]. These databases generally provide the average monthly irradiation and wind speed data, but in order to get the hourly time series data, various synthetic hourly estimation techniques are employed.

A. Solar Irradiation Hourly Data and Synthesis

Different index of solar irradiance exist which include

- Direct Normal Irradiance (DNI): Is the amount of solar radiation received per unit area by a surface that is always held perpendicular (or normal) to the rays that come in a straight line from the direction of the sun at its current position in the sky [10]. DNI is used to calculate Concentrating PV output. Concentrating PV uses optics to concentrate the solar radiation in a way that captures only the DNI and not the diffuse or reflected components of the incident solar radiation.[11]
- Global Horizontal Irradiance (DHI): Global Horizontal Irradiance (GHI) is the total solar radiation incident on a horizontal surface. It is the sum of Direct Normal Irradiance (DNI), Diffuse Horizontal Irradiance, and ground-reflected radiation. Solar GHI is usually used to compute flat-panel PV output [12].
- Diffused Horizontal Irradiance: is the amount of radiation received per unit area by a surface (not subject to any shade or shadow) that does not arrive on a direct path from the sun, but has been scattered by molecules and particles in the atmosphere and comes equally from all directions [10].

For sizing which require hourly solar irradiation readings, various estimation algorithms can be used to synthesis the hourly solar irradiation. Liu and Jordan [13] developed a theoretical hourly prediction model which synthesizes the average hourly solar radiation from the daily global radiation. This is given by

$$\frac{Id}{Hd} = \frac{\pi}{24}\frac{cos(w) - cos(ws)}{\left(sin(ws) - \frac{\pi ws\, cos(ws)}{180}\right)} \#(1)$$

$$\frac{I}{H} = \frac{\pi}{24}\frac{cos(w) - cos(ws)}{\left(sin(ws) - \frac{\pi ws\, cos(ws)}{180}\right)} \#(2)$$

Where I and Id are the average hourly and diffuse solar radiation on a horizontal surface expressed in KW/m^2 while w and ws are the hour angle and sunset hour angle expressed in degrees. V.A Graham [14] provided an estimation algorithm which has been used by some optimization tools like HOMER [15] to synthesis hourly solar irradiation from the average monthly irradiation. The algorithm requires the latitude and the twelve-monthly average values.Once the data set has been gathered either manually or synthesized, it is then inputted to various mathematical output models.

B. Wind Speed Hourly Data Synthesis

An accurate time series data of the weed speed is needed to accurately model the output power of a wind turbine. Physical methods of acquiring this time series data can be quite tedious as opposed to statistical methods which provides a fairly simpler and accurate estimate of the wind speed data [16]. These statistical methods are based on probabilistic and stochastic models. The common probabilistic models involve the use of Weibull distribution model or normal distribution model

1. Normal Distribution: This simply uses a sequence of random independent numbers from a normal distribution. It can be expressed as [17]

$$f(v) = \frac{1}{\sigma\sqrt{2\pi}} exp[\frac{(v-\mu)^2}{2\sigma^2}] \qquad (3)$$

Where v represents the hourly average wind speed (in m/s), σ represents the standard deviation of the wind speed (in m/s) and μ is the average value of the wind speed (in m/s).

2. Weibull Distribution: Aksoy in [17] described the Weibull distribution by the equation below;

$$f(v) = \frac{k}{l^k} * V^{k-1} exp[\frac{-1}{l^k} V^k] \quad (4)$$

Here V is the hourly average wind speed (in m/s), k is the shape factor while l is the scale factor. Stochastic models include autoregressive moving average (ARMA), wavelet based approach and Markov chain [17]

3.Autoregressive Moving Average (ARMA): It consists of three linear stochastic models namely autoregressive (AR models), moving average (MA) models and mixed (ARMA) models that combine autoregressive and moving average processes.

$$v_t = u_1 v_{t-1} + u_2 v_{t-2} + \cdots + u_n v_{t-n} + \varepsilon_t - o_1 \varepsilon_{t-1} - o_2 \varepsilon_{t-2} - \ldots o_m \varepsilon_{t-m} \#(5)$$

ARMA models account for the fact that hourly wind speeds are independent of each other, meaning they incorporate the chronological nature of the actual wind speed but with a degree of persistence [18].The ARMA series model is described below [19], Where u_i(i = 1,2,…n) = auto-regressive parameter, o_j (i = 1,2,…m) = moving average parameter, ε_t represents white noise process with an average of zero and variance of σ^2

4. Markov Chain: Here Stochastic processes are discretized into a number of states and the definitions of the probabilities for the inter-state transition. The transition probability matrix of a first-order Markov chain with n states is defined by [17]

$$P_k = \begin{bmatrix} P_{k11} & P_{k12} \ldots \ldots \ldots \ldots P_{k1n} \\ P_{k21} & P_{k22} \ldots \ldots \ldots \ldots P_{k2n} \\ . & . \qquad\qquad . \\ . & P_{kij} \qquad\qquad . \\ P_{kn1} & P_{kn2} \ldots \ldots \ldots \ldots P_{knn} \end{bmatrix} \#(6)$$

Where P_{kij} is the probability of transition from state I to state j. If m_{ij} is the total number of hours of observation in state j with the previous state I, the probabilities of transition from state I to state j is [17]

$$P_{kij} = \frac{m_{ij}}{\sum_j m_{ij}} i,j = 1,2,....n \quad (7)$$

Other methods used to generate time series wind speed data include the use of Fuzzy logic [20], Artificial Neural Network[21].

III. Load Demand Data

Optimal sizing is done with the goal of meeting the energy demand of a particular area, and as such an idea of the load profile is very important. In order to get the load profile, the hourly load or energy demand is required. This can be gotten directly from the distribution transformer feeding the area of interest. In cases where the yearly hourly load demand is not available, the load demand of another location that shares similar characteristics as the location of interest could be used. From the load profile, the base load, peak load, average and max load can be determined.

IV. System Specifications:

Depending on the component configuration of the hybrid energy system (HES), various specification data are needed such as efficiency of PV module, converters, wind turbine, fuel cost of generator, per unit cost of various equipment etc. Fig.3 shows the basic input data needed for optimal sizing.

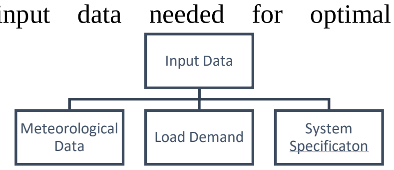

Fig 3 Required Data Needed for Optimal Sizing

V. Modelling of Hybrid Energy Sources

Various Energy sources such as solar PV, wind turbine, diesel generators, biomass etc can be hybridized Some of the most common renewable hybrid energy resources used are the photovoltaic and wind energy sources. And based on their wide spread usage, the various methods of modelling their outputs shall be discussed. It is very important to have an accurate result of the output power of each of the energy sources, and as such accurate modelling is necessary.

A. Solar-Photovoltaic Energy System

In order to model the output of a solar PV for a particular location, various data are needed such as the location's solar irradiation and temperature, depending on the model being used. Manually measuring solar irradiation and temperature data for a particular location is one of the best and accurate ways to get solar data, but due to how tedious and expensive the process is, especially for developing nations, other means of acquiring reliable data are commonly used. One reliable data source is Power Access Data Viewer by the U.S National Aeronautic Space Agency(NASA).A common mathematical model used by researchers in [22] and commercial sizing simulation tools like HOMER to calculate the output Photovoltaic (PV) power based on solar radiation and temperature is described below;

$$Ppv = Ypv * Fpv * \left(\frac{Gt}{Gstc}\right) * (1+ \propto (Tc - Tstc)) \quad (8)$$

Where Ppv is the Rated Capacity of PV array (in KW), Fpv accounts for the derating factor (in %), Gt is the solar radiation incident on the PV panel (in KW/m^2) , Gstc is the incident radiation at standard test condition (1 KW/m2) , $\propto$ is the temperature coefficient of power in (%/oC) while Tc and Tstc represent the PV cell temperature and PV cell temperature at standard test conditions.

In order to account for the surface area Apv (in m^2) we have

$$Ppv = Ypv * Fpv * Apv\left(\frac{Gt}{Gstc}\right) * (1+ \propto (Tc - Tstc) \quad (9)$$

And when considering the efficiency of the reference efficiency of the PV cell ηstc and efficiency of maximum power tracker $\eta mppt$ if applicable we have [23],[24],[25];

$$Ppv = Ypv * Fpv * \eta mppt * Apv\left(\frac{Gt}{Gstc}\right) * \left(1+ \propto (Tc - Tstc)\right) (10)$$

Another Solar-PV model used in modelling the output power of a PV is given by[26][27]

$$P_{pv(t)} = V_{pv(t)} * {I^{av}}_{pv(t)} \# (11)$$

Where

$${I^{av}}_{pv(t)} = n_p I_{rs(t)}\left[exp\left[q(V_{pv(t)} + I_{pv(t)}R_s\right] - 1\right] \# (12)$$

$$I_{ph(t)} = (I_{sc} + K_t\left(T_{(t)} - T_r\right) * \frac{\lambda_{(t)}}{1000} \quad (13)$$

$$I_{rs(t)} = I_{or}\left(\frac{T_{(t)}}{T_{ref}}\right)^3 exp\left[\frac{qE_{go}\left(\frac{1}{T_r} - \frac{1}{T_t}\right)}{KT_{(t)}}\right] \# (14)$$

$$I_{pv(t)} = I_{ph(t)} - I_{rs(t)}\left[exp\left[\frac{q(V_{pv(t)} + I_{pv(t)}R_s)}{A_c KT_{(t)}}\right] - 1\right] \# (15)$$

I_{pv} represents the current source, I_{ph} represents the generated current under a given insolation.I_{rs} is the reverse saturation current, V_{pv} is the PV panel array voltage level, q is the electron charges, $R_s$is the PV cell intrinsic resistance, A_c is the deviation of the cell from the ideal p-n junction, while K is the Boltzmann constant and T represents the cell temperature.I_{or} is the reverse saturation current, $T_r$is the reference temperature, $E_{go}$is the bandgap energy of the semiconductor cell used.$I_{sc}$is the short-circuit current at T_r while K_t and λ represent the short circuit current of temperature and insolation in mW/cm^2

B. Wind Energy System

Modelling the output power from a wind turbine generator requires accurate estimate of the wind speed at hub height. Once the time series wind speed data has been generated either physically or through probabilistic, statistic and artificial intelligent means, it is inputted into the wind turbine power output model.

Quite often, the wind speed data at a particular tower height is needed. One method used to determine this is the power law. The power law converts the wind speed at a particular hub height to the wind speed at tower height. The power law is given by [28];

$$V_{(t)} = V_{ref(t)} * \left(\frac{h}{h_{ref}}\right)^{\gamma} \#(16)$$

Where $V_{(t)}$ is the wind speed at the projected tower height h, and $V_{ref\,(t)}$is the wind speed at the reference height h_{ref} .The output of a wind turbine WT can be modelled according to [29]

$$Pwt(t) = \begin{cases} 0 & V_{(t)} < V_{ci} \\ a.V_{(t)}{}^{3} - b.Pwt^{r} & V_{ci} \leq V_{(t)} < V_{r} \\ Pwt^{r} & V_{r} \leq V_{(t)} < V_{co} \\ 0 & V_{(t)} > V_{co} \end{cases} \#(17)$$

Where$a = \frac{Pwt^{r}}{(V_{r}{}^{3} - V_{ci}{}^{3})}$ and $b = \frac{V_{ci}{}^{3}}{(V_{r}{}^{3} - V_{ci}{}^{3})}$

Where $V_{(t)}$is the wind speed at time t (in m/s), Pwt^{r} represents the rated power of the wind turbinein(W), V_r is the rated speed (in m/s), V_{ci} represents the cut-in speed (in m/s) and V_{co} is the cut-out speed of the WT in (m/s). This model has been used by authors in [23][25][24].

Another model which has been used to model the output power of a wind turbine is given by[30]

$$E_{wg\,(t)=}\, z_f * P_{wt-out}\left(1 - \propto_{for}\right)\Delta t \#(18)$$

Where z_f represents the altitude factor,P_{wt-out} is the power output of the wind turbine generator and $\propto_{for}$ is the forced outage rate. $\left(1 - \propto_{for}\right)$ represents the probability of the wind turbine being operational.

C. Battery Storage Model

Most hybrid energy systems usually consist of one form of energy storage or the other. The Battery energy storage is the most common energy storage method used in literature by researchers. One important parameter to consider when modelling battery energy storage is the depth of discharge DOD. A battery's capacity with respect to the DOD is given by [31];

$$C_{bat} = \frac{P_{load} * D_s}{DOD_{max} * \gamma_s} \#(19)$$

C_{bat} represents the battery capacity in Ampere-hours, P_{load} is the load, DOD_{max} is the maximum depth of discharge.

[32] used the following model to the charge and discharge capacity of a battery at any time t.

During the charge mode

$$E_{B(t)} = E_{B(t-1)}(t - \sigma) + \left(E_{GA(t)} - \frac{E_{l(t)}}{\gamma_{inv}}\right)\gamma_{batt} \#(20)$$

During the discharge mode

$$E_{B(t)} = E_{B(t-1)}(t - \sigma) - \left(\frac{E_{l(t)}}{\gamma_{inv}} - E_{GA(t)}\right)\gamma_{batt} \#(21)$$

Where $E_{B(t)}$ and $E_{B(t-1)}$ represent the battery charge at time t and (t-1), σ is the hourly self-discharge rate, $E_{GA(t)}$ represents the total energy generated by the hybrid energy system. E_l is the load while γ_{batt} and γ_{inv} are the battery bank and inverter efficiency respectively.

D. Diesel Generator Model

The most common non-renewable power source used in hybrid energy systems is the diesel generator. Its use however is gradually reducing due to environmental concerns, based on the fact that it is powered by fossil fuel-based energy source. Regardless, of this, the diesel generator can be used as a useful back-up system. In the design of hybrid energy systems that include diesel generator (or any other fossil-fuel based generator), the diesel generator is usually given the lowest priority, meaning the generator is only used after all energy from all the renewable energy source and storage have been depleted. The fuel consumption rate F of the generator, with its output power is given as[33];

$$F = F_0 * Pr_{dg} + F_1 * P_{dg} \#(22)$$

Where F_0 is the fuel curve intercept coefficient, F_1 is the fuel curve slope, Pr_{dg} is the rated capacity of the generator and P_{dg} is the electrical power output of the diesel generator.

VI. Optimal Sizing objectives and index for Hybrid Energy Systems

The major objective for sizing of HES, has been to minimize the cost while maximizing the reliability index. Over the years, various forms of cost objective function and reliability index have been considered. Some of which are discussed here.

A. Reliability Index:

Hybrid Energy system usually consist of some renewable energy components. Some Hybrid Energy Systems are purely renewable. The presence of renewable energy brings about the problem of intermittency, since the primary energy sources are not always available and as such, the reliability of the of such system is of high importance. Reliability here is the guarantee that the hybrid energy system would adequately supply power to meet the load demand. Reliability is usually considered either as a constraint in the problem or an objective to be achieved. Various reliability indices have been used in several literatures involving sizing of Hybrid Energy System (HES). Some of these reliability indexes shall be discussed;

1. Loss of Power Supply Probability: Loss of power supply probability (LPSP), is the probability that a loss of power occurs, meaning the combined energy system is not able to supply the load demand. It is a good measure of performance of the system for an assumed or known load distribution and other system parameters [34].It is expressed as [23]

$$LPSP = \frac{\sum_{t=0}^{T} LPS_{(t)}}{\sum_{t=0}^{T} P_{load}} = \frac{\sum_{t=0}^{T} Power\ Failure\ Time}{T} \#(23)$$

Where LPS is the loss of power supply and it is given by;

$$LPS_{(t)} = P_{load\ (t)} - \sum P_{hybrid\ (t)} \#(24)$$

LPSP is by far the most common reliability index used by researchers. Several authors have considered LPSP when designing their systems. [35] considered the probability of power loss when carrying out the technical feasibility (which involved optimal sizing) on a stand-alone hybrid wind-solar system with pumped hydro storage for a remote island in Hong Kong. He was able to achieve a LPSP of 0.4% when the upper reservoir of the pumped hydro decreases by 4000m3. [36] carried out optimal sizing of an hybrid solar-wind-battery system to supply power to a telecommunication relay station and one important constraint was to achieve a certain required loss of power supply probability. The Loss of power supply probability was also considered as a performance constrain by [37], where optimal sizing of a wind-solar-battery hybrid system was considered.

2. Expected Energy Not Served: The Expected Energy Not Served (EENS) is defined by[38]as the expected amount of energy not being served to consumers by the system during the period considered due to system capacity shortage or unexpected severe power outages.[39] carried out a stochastic performance assessment, involving sizing and reliability analysis of a hybrid power system including renewable sources and energy storage, while considering the Expected Energy Not Served. EENS is expressed as[39]

$$\boldsymbol{EENS} = \frac{\sum_{n=1}^{N} ENS}{N} \#(25)$$

Where ENS is the Energy Not served expressed as; $ENS = \sum_{t=1}^{T} L_t$, L_t is the load not met.

3. Loss of Load Probability (LLP): This is expressed as [40]

$$LLP = \frac{\sum_{i=1}^{T} ES_{(t)}}{\sum_{i=1}^{T} LD_{(t)}} \#(26)$$

Where ES is the Power shortage at time t and LD is the load demand.

B. Cost Objective Function:

In optimal sizing problems, the objective is to meet the energy demand at a minimized cost while considering several constraints. And as such, the cost is very important. Different cost objective function to be minimized have been developed in the past such as the levelized cost of energy (LCOE), Lifecycle or Net Present cost and the annualized cost.

1. Levelized Cost of Energy: Levelized cost of energy (LCOE) measures lifetime costs divided by

energy production. It calculates the present value of the total cost of building and operating a power plant over an assumed lifetime and allows the comparison of different technologies (E.g. wind, solar, natural gas) of unequal life span, project size, different capital cost, risk, return and capacities [41]. Researchers in [42][43] considered the levelized cost of energy when tackling the optimal sizing problem. It can be expressed as[44]

$$LCOE = \frac{Total\ Net\ Present\ Cost}{\sum_{t=1}^{T} \boldsymbol{P_{load(t)}}} * CRF\#(\mathbf{27})$$

CRF is the capital recovery factor, and it is given below;

$$CRF = \frac{i(1+i)^n}{i(1+i)^n - 1}\#(28)$$

Where I isthe interest rate and n is the system life period.

From the equations above we can see that the levelized cost of energy is related to the net present cost.

2.Net Present Cost: The Net present cost (NPC) is also known as the Life-cycle cost. It is the present value of all the costs of installing and operating the Component over the project lifetime, minus the present value of all the revenues that it earns over the project lifetime [45]. Some of the literatures which employed the Net Present cost are [46]–[50]. It is expressed as [51];

Total NPC = $C_{investment}$+ OM_{npv}+ R_{npv}-S_{npv}

(29)

Where Cinvestment is the capital cost of investment, OMnpv is the operations and maintenance cost, Rnpv represents the replacement cost while Snpv is the salvage value. “npv” denotes the net present value of each factor.

VII. Sizing Optimization Algorithms and Methods

Various optimization methods/techniques have been used over the years to tackle the optimal sizing problem. From the various literature reviewed we can classify the methods as;

- Artificial Intelligence (and Meta-Heuristic) Optimization Algorithms
- Commercially Available Optimization Tools

A. Artificial Intelligence (and Meta-Heuristic) Optimization Algorithms

Of all the Artificial Intelligence (AI) available, the use of meta-heuristic algorithms has been a common trend in optimal sizing. Although it is expected that in future, Machine Learning would be extensively used to carry out optimal sizing of hybrid energy systems[52]. The prospect for machine learning are enormous and it is currently being used in estimation of time series solar irradiation and wind speed[53][54] . Various types of meta-heuristic optimization techniques have been used in the past to solve the optimal sizing problem and at the same time there exist algorithms such as cultural algorithm, shark-smell algorithm which have not yet been tested in solving the optimal sizing problem. It can be observed that the most common meta-heuristic method used in past literature has been the genetic algorithm and the particles warm optimization algorithm and their variants. Some of these meta-heuristic techniques would be discussed further.

1. Genetic Algorithms

Genetic Algorithms (GA) are an evolutionary based computational optimization technique which was first introduced by John Holland in 1970. GAs code the candidate solutions of an optimization algorithm as a string of characters which are usually binary digits. GAs are theoretically and empirically proven algorithms that provide a robust search in complex spaces, thereby offering a valid approach to problems requiring efficient and effective searches. Any GA starts with a population of randomly generated solutions (chromosomes) and advances toward better solutions by applying genetic operators, modeled on the genetic processes occurring in nature[55]. Genetic Algorithms and its variants have been used extensively for optimal sizing. The modelling, simulation and optimal sizing of an hybrid energy system consisting of wind, solar PV and battery was carried out by [56], he used a parallel multi-deme implementation of genetic algorithm to carry out the optimization and the work was applied in Northern

Kenya. Genetic Algorithm was also used by [36] to optimally size a standalone hybrid solar wind system using the loss of power supply probability as the reliability index. The hybrid system was applied to supply power to a telecommunication relay station. [56] also used genetic algorithm for optimal sizing of hybrid power system containing wind farm, Photovoltaic (PV), diesel generator and battery bank. Here the author looked at minimizing the cost including inflation, capital recovery factor and sinking found factor. Binary genetic algorithm was applied by [48] in solving the optimal sizing problem for a small autonomous hybrid power systems. [57] also used genetic algorithm in optimal sizing and energy management for a hybrid of PV and wind. General Parallel Genetic Algorithm (GPGA) was used by [58] in determining an optimal sizing and operations strategy of energy storage system. Here GPGA was used to estimate the optimal ratings of multiple energy storage units and photovoltaic (PV) generators in order to minimize distribution energy losses, annual energy and peak power supplied by the substation transformer.

2.Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a swarm based stochastic optimization technique proposed by Eberhart and Kennedy in 1995. It mimics swarm behaviors of animals such as a flock of birds or school of fishes[59]. Just like GA, PSO has been extensively applied to optimal sizing and it is one of the most common algorithms used in optimization of hybrid energy systems.[60], carried out the optimal sizing and control strategy of a hybrid energy mix consisting of Photovoltaic (PV), diesel and battery using the Particle Swarm Optimization technique. Here the objective was to minimize the cost associated with CO2 emissions and customer damage cost function for the compensation cost due to the electricity shortages. [61] achieved efficient optimal sizing of a standalone wind/photovoltaic hybrid energy mix using Particle Swarm Optimization (PSO), the objective here was to minimize the overall cost of the generation scheme over 20 years of operation. A multi objective PSO was used by [62] in determining the optimal component size. The work also applied energy management in addition to optimally sizing and Sweden was used as a case study. In [44] optimal sizing and power management was carried out with the aid of a Multi-Objective Particle Swarm Optimization technique (MOPSO) for a micro grid. Also, particle swarm optimization was applied by [50] in optimally sizing of hybrid renewable energy system, and the study was performed for Kahnouj area in south-east iran. The system also consisted of fuel cells, wind units, electrolyzers, reformer, anaerobic reactor and hydrogen tanks. It also used biomass energy sources.

3. Grey Wolf Optimization

Grey wolf optimization is a recent swarm intelligence-based algorithm. It is inspired by grey wolves in nature when in search of the optimal way to hunt their preys [63]. The grey wolf optimization technique has not been used as extensively as the genetic and particle swarm optimization technique in solving sizing problems. From literature, grey would has been used majorly in sizing of energy storage systems and for energy management. [64] used grey wolf optimization to determine the optimum energy management and battery sizing method for a grid connected micro grid. Also [65] used grey wolf for optimal sizing of battery energy storage to minimize the cost of operation of micro grid.

4. Firefly Optimization

The Firefly Algorithm has two important variables which are the light intensity and attractiveness [66]. Authors [67] used the firefly meta-heuristic algorithm optimization technique in carrying out the optimal sizing of a hybrid power system (HPS) consisting of wind, solar PV and battery. With the objective of minimizing the total annual cost and supplying annual load demand. The Firefly (FA) algorithm was also used by [68] for minimizing the generation cost of a microgrid. The microgrid considered here consisted of both renewable and conventional generating units. [69] minimized the cost of operation in a microgrid using the firefly algorithm. The energy sources considered here included fuel cells, photovoltaic (PV), micro turbine and wind.

5. Artificial Bee Colony

The Artificial bee colony (ABC) is a population-based swarm intelligence technique proposed by karaboga in 2005. This meta-heuristic algorithm is based on the spontaneous food foraging behavior of the honey bee. [70] .ABC optimization technique was used by [71] to optimally size the various microgrid components which includes solar PV, wind turbines, and energy storage. The objective here was profit maximization. [72] also used the artificial bee colony optimization technique for sizing hybrid energy sources consisting of PV and biomass.

6. Using Hybrid Algorithms

Several researchers over the years have also used various hybrids of meta-heuristic algorithms in order to achieve more accurate results. Researchers [42]used a hybrid of genetic algorithm and particle swarm optimization GA-PSO for optimal sizing of the hybrid energy mix consisting of PV, wind, and battery banks. The authors also performed the same study using a multi-objective particle swarm optimization algorithm and validated the results using the Hybrid optimization for multiple energy resources (HOMER).Also a hybrid algorithm of fuzzy-adaptive genetic algorithms have been used by authors in [22], [73].

B. Commercially Available Optimization Tools

In addition to the use of artificial intelligence backed meta-heuristic optimization algorithms, several optimization tools have been developed to design, analyze and optimize hybrid energy system on economic and technical basis. The Hybrid Optimization of Multiple Energy Resource (HOMER) is a very common tool used in sizing of hybrid energy systems for micro-grid. HOMER performs a techno-economic analysis[74], with the Net Present Cost (NPC) being the main economic cost objective to be minimized. Basically, HOMER ranks its configuration based on the NPC. One advantage that HOMER has is that it offers a free-month trial to its users and this has helped increase its usage and popularity amongst researchers and engineers. Latest version of HOMER have improved features of considering the unreliability of grid systems when optimally sizing a grid connected HES. HOMER was developed by Dr. Lilienthal at the National Renewable Energy Lab (NREL)[45]. HOMER can also be used to synthetically generate hourly solar, wind and temperature time series data.

Another Tool to note is the Improved Hybrid Optimization by Genetic Algorithm (iHOGA)which was developed at the Universidad Zaragoza by Dr. Rodolfo Lopez.iHOGA was developed based on C++ and can perform simulation and optimization of both stand-alone and grid connected Hybrid Energy Systems (HES)[75].iHOGA is capable of performing both single and multi-objective optimization using Genetic Algorithm[76].iHOGA also has a free (EDU) version but with limited features, as it cannot simulate a system with load greater that 10kWh. Some iHOGA based research include[77][78].

HYBRID 2, is an optimization tool programmed in Microsoft Visual BASIC and uses Microsoft Access Data base. It was developed at the University of Massachusetts with suppor from the National Renewable Energy Laboratory in 1996. HYBRID 2 allows systems based on three buses containing wind turbines, PV array, diesel, battery storage, power converters and a dump load[76].Other Notable tools of mention include SOMES developed at Utrecht University Netherlands, SOLSIM developed by Fachhochschule Konstanz, INSEL developed at University of Oldenburg and TRNSYS[51]. Although the HOMER and iHOGA software are the most common tools which have been extensively used and widely accepted.

Fig 4 shows a top-down flowchart showing the process of optimal sizing from data acquisition to obtaining results..

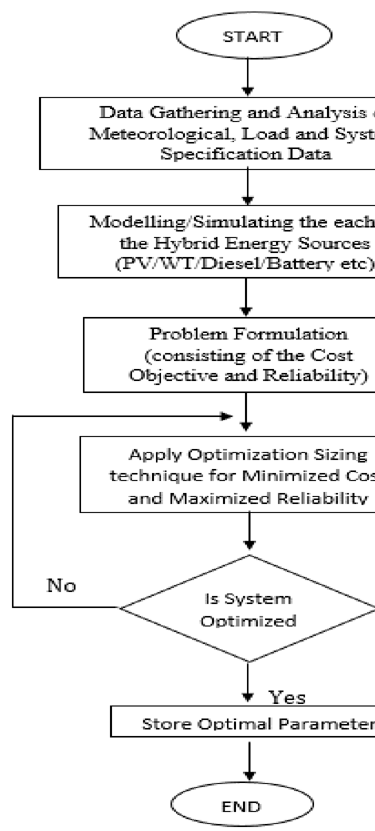

Fig 4 Flow Chart Showing the General Optimal Sizing Methodology

VIII. CONCLUSION

Hybrid Energy System provide a reliable means of supplying power, especially to (developing) areas that suffer from erratic power supply or that are not connected to the grid. Hybrid Energy Systems with purely renewable energy system offer an extra advantage over conventional grid supply in terms of offering clean reliable energy. Hybridizing energy sources helps in providing emission-free power supply, and in cases where non-renewable sources are considered, hybridizing helps to reduce the amount of fossil fuel that would have been used. Conventional grid supply still offers cheaper power compared to Hybrid Energy Systems, and as such optimal sizing of hybrid energy system for minimized cost is quite important while considering reliability. Also, the current improvement in battery, solar and wind technology makes a good case for hybrid renewable energy systems (HRES).

In this work, the various mathematical models of the commonly used hybrid energy sources have been reviewed, also methods of gathering and synthetically generating meteorological weather data has been discussed. The various methods for optimizing hybrid energy systems has also been discussed, we can notice a trend where various meta-heuristic algorithms are being tested to solve the optimal sizing problem, regardless, the genetic algorithm (GA) and particle swarm optimization (PSO) are the most common meta-heuristic optimization used for optimally sizing of hybrid energy systems due to their fast convergence rate and short computational time, and they have proven to be quite effective and accurate. HOMER is the most commonly used optimization tool for sizing, closely followed by iHOGA due to their ease of access, free trial feature, and robustness. Also, we see that very little work has been done using machine learning methods for optimal sizing. It is recommended that in future machine learning algorithms be tested for optimal sizing. This review is relevant to researchers, engineers and all those involved in the design of micro-grids, as it presents an overview of the recent trends and methods involved in optimally sizing hybrid energy sources for microgrid applications.

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