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AHREPS - Alternating Hybrid Renewable Energy Power System for Load Prioritization: A Case Study of Otokwu-Mmaku Community, Awgu, Enugu State, Nigeria

Anikpo Chukwuka Ekene, Ogbonna Bartholomew Odinaka

Department of Electrical/Electronic Engineering, University of Port Harcourt, Port Harcourt, Nigeria

Email address:
anikpochukwuka@gmail.com (Anikpo Chukwuka Ekene), bartholomew.ogbonna@uniport.edu.ng (Ogbonna Bartholomew Odinaka)

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Abstract: This paper presents the results of a research study using a novel Binary Data Driven Programming (BDDP) solution coined AHREPS (Alternating Hybrid Renewable Energy Power Systems) to alternate between a Solar Photovoltaic (Solar PV) Renewable Energy (RE) system and a Wind Turbine (WT) Renewable Energy system to provide continuous power supply in a rural-to-suburban household at Otokwu Mmaku Community, Awgu, Enugu State, Nigeria. The computational model for the Otokwu-Mmaku Solar PV (OMPV) and Otokwu-Mmaku Wind Turbine (OMWT) hybrid renewable energy (RE) systems are data-driven by a synthesis of data from simple function-fitted models to a generalized polynomial of order-1 for a 4-year duration (2018 to 2021). The results considering an average baseline load of 0.9kWh/day showed that using a 3-parallel connected 200W Solar PV modules and 5kW Wind turbine modules; the AHREPS employed the OMPV RE system for the months of January through June and the months of September through December all through the 4-year duration (2018-2021) but in the months of July (2021) and August (2020), the AHREPS employed the OMWT RE system in providing continuous power supply for the estimated load. This clearly shows that considering the model selection and alternating effects of the hybrid RE systems, the proposed AHREPS model can effectively meet the expected load demand of the aforementioned location.

Keywords: Alternating Hybrid Renewable Energy Power System, Otokwu-Mmaku Solar Photovoltaic, Solar Energy, Otokwu-Mamku Wind Turbine, Wind Energy, Renewable Energy, Solar Photovoltaic, Wind Turbine

1. Introduction

Renewable energy resources like the solar and wind turbine is fast becoming the energy solution of the future.

Both systems can produce direct current and can be converted to alternating current using the inverter or generators. In addition, both energy sources have demonstrated to be a good source of renewable energy and more than likely, to provide sustainable and affordable sources of alternative energy [6].

However, due to large variability of the energy potentials of the aforementioned sources in their seasonal cycles, the amount of power output generated by the individual energy systems may not be able to support pre-specified baseline load demands.

Thus, popular approaches now embrace hybrid solutions some of which employ probabilistic, iterative, linear programming or Artificial Intelligence (AI) techniques [9].

The implication is a that there is no one solution that does it all in the field of Renewable Energy (RE) research for power supply maximization.

In this research, an approach that exploits the principle of alternating between two hybrid RE sources coined AHREPS (Alternating Hybrid Renewable Energy Power Systems) in a hybrid context including a Solar Photovoltaic (Solar PV) system and a Wind Turbine (WT) generator for meeting the load demands of a typical rural-to-sub-urban household in Otokwu Mmaku Community, Awgu, Enugu State, Nigeria is investigated.

The approach is data-driven and utilizes a binary programming logic to infer the likely state representations of both renewable schemes in their individual and alternating forms.

In subsequent section (Section 2), the review of related studies in the field of renewable energy is presented. In Section 3, the proposed methodology used in this research is presented. In Section 4, the results and discussions are presented and in Section 5, the conclusions are given.

2. Related Studies

In the field of renewable energy, quite a number of researches have been carried out in the context of energy potential determination and implementation in an off-grid context [12].

For instance, in the research study; prioritized rule based load management technique for residential building powered by PV/battery system, simple models were employed for the development of a Stand-alone Solar PV Battery (SAPVB) system to serve different rural centers [2].

In the feasibility study of renewable energy-based micro-grid systems in Somaliland, hypothetical investigations on the feasibility of providing a renewable energy system to a small suburban area in Hargeisa, a major urban center in Somaliland was performed. They carried out a techno-economic analysis to evaluate the economic prospects of renewable energy in the region. In this regard, a software tool - Hybrid Optimization Model for Electric Renewables (HOMER), was used to determine renewable energy (RE) penetration levels [1].

The Techno-economic analysis of a hybrid system for rural electrification in Cambodia considered shortage of electricity in developing countries as the main obstacle for economic and social development. Cambodia was used as a case study and it was observed that isolated grid diesel-based systems were used for rural electrification. Their work was aimed at investigating the optimum scenario of a hybrid system for supplying electricity to one remote district in Cambodia [8].

Again, Hybrid Optimization Model for Electric Renewables (HOMER) was used as a tool for techno-economic analysis. Three scenarios are considered in this study: diesel-only; diesel/PV; and diesel/PV with battery system. Results showed that diesel/PV with battery were the optimum solution [14].

The feasibility of a proposed Stand-alone SolarPV/Battery (SAPVB) system over the existing (commonly used) fuel-powered gen set called “I pass-my-neighbor” generator was investigated in order to meet the small power needs of a typical rural household in Nsukka, Enugu State, Nigeria was studied [3].

Using the HOMER® PRO software and considering the economic and environmental aspects of the proposed existing energy systems, the author found that the proposed SAPVB system whilst being able to meet the expected small power needs incurred a very high initial capital cost over several hundreds of thousands of Naira. This may be attributed to the high cost of batteries and SolarPV modules, the key components of the SAPVB system [3].

Again, In terms of environmental impact, it was found that the SAPVB system generated 100% clean energy with no fuel consumption issues as compared to the gen set option which resulted in heavy pollution and fuel usage for a project lifetime of 25 years. [15].

In the Novel Energy Management Scheme using ANFIS for Independent Micro-grid, an energy management technique for Hybrid Renewable Energy System (HRES) was connected with AC load using Adaptive Neuro Fuzzy Interference System (ANFIS). This algorithm was developed with an aim of increasing the power transfer capability between the source side and load side and it offers several benefits like the enhanced predicting capability, degradation in complexity as well as the randomization and so forth. In this work, photovoltaic (PV) system, Wind Generating System (WGS), Fuel Cell (FC), Ultra Capacitor (UC) and the battery are considered as the energy sources [4].

The impact of a hybrid Solar/Wind RE/Diesel-gen set system when compared to a Diesel-only gen set option to power a typical rural health clinic in three different (regional) parts of Nigeria was studied [10]. Their study adopted the HOMER ® PRO software sequential optimizer strategy for evaluating the economics and environmental viability of the considered systems for a project lifetime of 20 years. From simulation results, the author found that though the Wind option did poorly in one of the sites, the combination of Solar/Wind RE/Diesel-gen set is a more viable option for the considered project lifetime when compared to the highly costly and environmentally unclean Diesel-only-gen set option.

Simulations were carried out to determine the effectiveness of innovative solar technologies in the structures of an existing building in Bari, Italy [5]. They investigated the effect of replacing the standard clear glass windows with perovskite-based semi-transparent PV modules and also the replacement of the original transparent shading system with high performance opaque perovskite-tandem cells. They reported a yearly PV energy savings estimation of 18% without buildings obstructions (ideal condition) and a savings reduction of 4% with nearby building obstructions [5].

The research study; prioritized rule based load management technique for residential building powered by PV/battery system and their scheme comprised 4 scenarios for a possibly satisfaction of critical and uncritical load class; in this scenario list, the first scenario served as the base and it did not include any optimized rule strategy. Using a Genetic Algorithm (GA) optimizer, optimal combination of load units in a sequence of critical load classes could be met by considering an objective that allows the load demand to be matched by power availability. The results of their simulations showed that the second to fourth scenarios were able to meet the load demand using the optimized SAPVB system.

A comparison was made for many optimization techniques of the hybrid renewable energy systems. For remote areas which represent most of the standalone application for hybrid solar PV and wind systems, it is not always easy to find long-term weather data, such as solar radiation and wind speed that are used for sizing purposes. Hence, more artificial intelligence techniques such as fuzzy logic, genetic algorithms and artificial neural networks are used for sizing standalone systems in comparison with traditional sizing method based on long-term weather data. [11, 13].

A proposed methodology for optimal sizing of stand-alone PV and wind generator systems to minimize the 20-year total system cost was also analyzed [7]. This included the number of battery chargers, PV modules, tilt angle and wind generator installation height that highly affect the resulting energy production and the installation and maintenance costs. [7].

3. Methodology

The methods employed include the power output model calculations for the Solar Photovoltaic (Solar PV) and Wind Turbine (WT) solutions, the Wind Power-Velocity linearization process model and the AHREPS Binary-Data-Driven Programming (BDDP) model logic. The design calculations are meant to determine the individual model's power contributions while the AHREPS BDDP model logic is meant to determine when to switch between the two RE systems to meet the estimated load demand.

For the purpose of this study, the parameter values used in this study are as defined in Tables 1 and 2 for the Solar PV and Wind Turbine model systems respectively.

3.1. Solar PV Model

For a solar power system, the following model calculations are needed as the Standard Test Conditions (STC) [2, 10]:

$$P_{pv} = N_s \times N_p \times V_{oc} \times I_{sc} \times FF \tag{1}$$

N_s = number of PV modules connected in series

N_p = number of PV modules connected in parallel

V_{oc} = open circuit voltage of the PV module at STC

I_{sc} = short-circuit current of the PV module at STC

FF = PV module fill factor

P_{PV} = PV output power, kWh

and,

$$V_{oc} = V_{oc(stc)} - K_v T_c \tag{2}$$

$$I_{sc} = \left(I_{sc(stc)} + K_i \left(T_c - 25\right)\right) G \tag{3}$$

K_v = PV module open-circuit voltage temperature coefficient correction factor, *V/°K* at STC

K_i = PV module short-circuit current temperature coefficient correction factor, A/°*K* at STC

G= Global solar irradiance, kW/m^2

T_c = PV cell temperature, °*K*

The Solar PV module cell temperature, T_c, affected by the ambient temperature effects.

$$T_c = T_{amb} + \left(0.0256 \times G\right) \tag{4}$$

T_{amb} = ambient temperature, °*K*

3.2. Wind Turbine (WT) Power Model

To model the input-output state of a WT, the Kinetic model is considered [10]:

$$P_{WT} = 0.5 \times \rho \times A \times v^3 \times C_{p\max} \tag{5}$$

ρ = Air density, kg/m^3

A = Turbine swept area, m^2

v = Wind velocity, *m/s*

$C_{p\max}$ = Utilizing ratio

Table 1. *Power Model Parameters for Solar-PV Generator.*

Parameter	Value	Unit	Comment
Number of Series Connected PV Modules (N_s)	1	NA	Determined By Trial & Error
Number of Parallel Connected PV Modules (N_p)	3	NA	Determined By Trial & Error
Short-circuit current of the PV module at STC (I_{sc})	5.56	A	From Datasheet (Appendix B)
Open circuit voltage of the PV module at STC (V_{oc})	45.43	V	From Datasheet (Appendix B.)
PV Module Fill-factor (FF)	0.90	NA	From Datasheet (Appendix B.)
PV module open-circuit voltage temperature coefficient correction factor (K_v)	-0.37	*V/°K*	From Datasheet (Appendix B.)
PV module short-circuit current temperature coefficient correction factor (K_i)	0.03	*A/°K*	From Datasheet (Appendix B.)
Global solar irradiance (G)	{…}	kW/m^2	From NASA GIS repository
Ambient temperature T_{amb}	{…}	*°K*	From NASA GIS repository

Table 2. *Power Model Parameters for Wind-Turbine (WT) Generator.*

Parameter	Value	Unit	Comment
Air density (ρ)	1.225	kg/m^3	Standard Value
Turbine swept area (A)	32.17	m^2	From Datasheet (Appendix B.)
Utilizing ratio ($C_{p\max}$)	0.40	NA	From Datasheet (Appendix B)
Wind velocity	{…}	m/s	From NASA GIS repository

3.3. Wind Turbine (WT) Power-Velocity Model Curve Fitting Model

In order to further simplify the estimated power outputs from the expression of the WT, basing on the yearly wind velocities using eqn(5) may be alternatively described as a linear function of its wind speed using a curve-fitting model as:

$$P_{WT} = mv + k \tag{6}$$

m = The slope of the power-velocity curve obtained from the curve-fitting

k = A constant obtained from the curve-fitting

As can be seen, the expression in eqn (6) is more easier to understand for novice operators when compared to that given in eqn (5).

3.4. AHREPS Model Logic

The primary goal of AHREPS is to always provide an alternative RE source when one fails to provide the minimum energy support. This is based on a minimum-energy-entry (mee) barrier which must be met to activate the second RE resource.

The AHREPS is implemented as a data driven logic. The pseudo-code is given in Listing 1:

Listing 1: The AHREPS computational program

Begin:

Step 1: Compute the Wind and Solar Power densities, *Pwind* and *Psolar* for site using equations (1) and (2) as indicated above.

Step 2: Initialize AHREPS signaling variables: *modeWT*, *modePV*, *modeSelect* and *modeContribution*, *i*

Step 3: Run the AHREPS module logic:

```
for i = 1:n
if(Pwind(i) > Psolar(i))
modeWT(i) = 1;
modePV(i) = 0;
else
modeWT(i) = 0;
modePV(i) = 1;
end
end
modeSelect = [modeWT modePV];
modeContribution = (Pwind + Psolar) > 0.9; % > 0.9kW/hr - Daily-hourly Load
```

Step 4: Print Results to screen

End

The essence of AHREPS as demonstrated in Listing 1 is to identify firstly the winning renewable energy system based on the state representations of the Solar PV (modePV) module and Wind Turbine (modeWT) module.

These states are subsequently concatenated and represented as the mode Select parameter in their alternating state.

Secondly, the AHREPS program also serves the purpose of evaluating whether each of the RE systems meet the desired load demand threshold state in the additive sense.

In the considered dual logic as described in Listing 1, states may either take a value of 0 or 1 and this makes for a Binary-Data-Driven Programming (BDDP) solution.

4. Simulation Results and Discussions

The simulations considered the load profile adopted in the earlier work in table 3 below as the location exhibits similar characteristics to that used in this research study. The description of the proposed site is presented, followed by results considering the Wind Power-Velocity regression fitting and the AHREPS simulations for the period of 2018 to 2021.

4.1. Load Profile and Plant Specification

The load profile data used for initial studies are obtained from field studies for a typical rural House-Hold (HH) in equivalent location in Enugu State [3]. This data describes a simple power usage pattern comprising several electric bulbs (for lighting and security), a small Television (TV) set, and a small fan. The dataset is as described in Table 3 while the load profile is as shown in Figure 1.

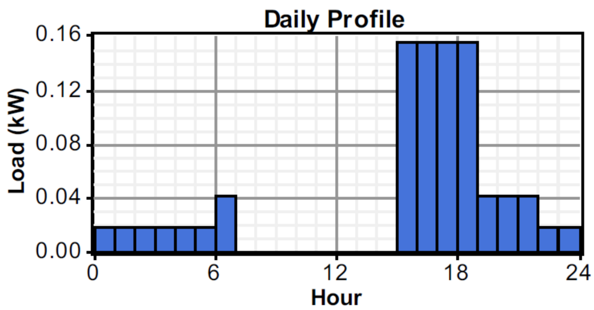

Figure 1. *Daily Load Profile Used for Study Site [3].*

Table 3. *Household Energy Use [3].*

Item Description	Quantity (Qty)	Load (W/Unit)	Total Load (W)	Hourly Utilization (hr/day)
TV	1	80	80	4
Fan	1	75	75	4
Electric bulbs (Lighting)	4	6	24	4
Electric bulbs (Security Light)	2	9	18	12

The load profile data points as shown in Figure 1 is entered into the HOMER Tool using the Electric Load component option to generate the HOMER load profile data as shown in Figure 2.

Figure 2. Daily Load Profile in the HOMER® PRO software interface.

As can be seen from the Figure 2, the average estimated daily consumption is at the baseline of approximately 0.9kWh/day. This is almost equivalent to a conventional "I better pass my neighbor" generator set. Hence, the estimated daily consumption will be a range of 0.7kWh/day as minimum rated and 0.9kWh/day as maximum rated.

The monthly-daily direct solar irradiance including temperature and the wind speed data for the study location for the year 2021 are as provided in Tables 4 and 5 respectively. Previous data for the period of 2018 to 2020 were also considered and these can be obtained from the NASA repository.

***Table 4.** Monthly average shortwave downward direct normal irradiance, I_{rravg} (kWh/m^2/day) with temperature, T (°C), 2021.*

Month	I_{rravg} (kWh/m^2/day)	T (°C)
Jan	5.350	26.130
Feb	5.250	26.430
Mar	4.810	26.570
Apr	5.610	26.970
May	4.860	26.440
Jun	4.710	25.750
Jul	4.160	25.080
Aug	4.230	25.120
Sep	4.140	25.180
Oct	4.840	25.690
Nov	4.940	26.120
Dec	5.050	24.870

***Table 5.** Monthly average wind speed, W_{speed} (m/s), 2021.*

Month	W_{speed} (m/s)
Jan	3.500
Feb	3.800
Mar	4.130
Apr	4.200
May	4.060
Jun	3.730
Jul	4.870
Aug	4.410
Sep	4.300
Oct	3.990
Nov	3.230
Dec	4.070

From the Tables 4 and 5, we see that the maximum average solar irradiance and wind speed for a given year are 5.61 kWh/m^2/day and 4.87 m/s respectively; the maximum values for the solar irradiation and wind speed also fall on April and July respectively. Correspondingly, the minimum average values obtainable for solar radiation and wind speeds are 4.14 kWh/m^2/day and 3.23 m/s. For these speed regimes (case of Wind Turbine – WT), the Hummer series H6.4-5KW WT generator was considered.

4.2. Wind Turbine Model Fitting Results

Considering the OMWT monthly-daily power computation, an updated Power Velocity Linear (PVL) model of the theoretical wind power density was utilized. This model was obtained using the MATLAB curve-fitting toolbox of the linear poly-order-of-1 and its expression and performance indicators – root-mean-squared-error (RMSE), R-squared (R^2) and Adjusted- R^2 are as described in Table 6.

For the entire years under study including 2018, 2019, 2020, and 2021, the PVL model of the OMWT is described by a combination of the computed curve fitting model for the individual years. This is achieved by adding up all the model expressions and dividing by the total number of considered years, in this case 4. The results of this particular case are as shown in Table 7.

Table 6. *PVL model and MATLAB curve-fitting performance indicators (2021).*

Parameter	Value (expression)
PVL Model	0.3873*v – 1.0290
RMSE	0.0330
R^2	0.9797
Adj.R^2	0.9777

Table 7. *Combined PVL model.*

Parameter	Value (expression)	Performance		
		RMSE (kW)	R^2	Adj.R^2
PVL Model (2018)	0.3449*v – 0.8398	0.033	0.9805	0.9785
PVL Model (2019)	0.3337*v – 0.8113	0.024	0.9815	0.9797
PVL Model (2020)	0.3659*v – 0.9207	0.049	0.9644	0.9609
PVL Model (2021)	0.3873*v – 1.0290	0.025	0.9797	0.9777
Mean	0.3579*v – 0.9002	0.033	0.9765	0.9765

From the Table 7, it can be inferred that the best PVL model is the 2019 model with an RMSE of 0.024kW, R^2 of 0.9815 and an Adjusted R2 (Adj.R^2) of 0.9797. Also, it can be seen that the overall (mean) PVL representation of the proposed site is 0.3579*v – 0.9002 which will be used as an approximation to onsite power valuation of the OMWT.

4.3. Monthly Load Profile Results

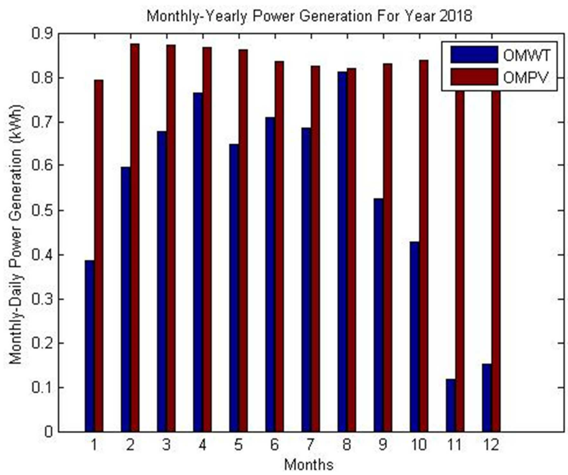

Figure 3. *Monthly-Daily Generation for 2018.*

The monthly-daily power generations for both systems (OMWT and OMPV) for the considered years are computed using the model expressions for the computation of the Solar-PV system as described in Section 3 (Section 3.1) and the updated Wind-Velocity model as described in the previous sub-section (sub-section 3.3). The results are as shown in the Figures 3 to 6 for the years 2018 to 2021 in that order.

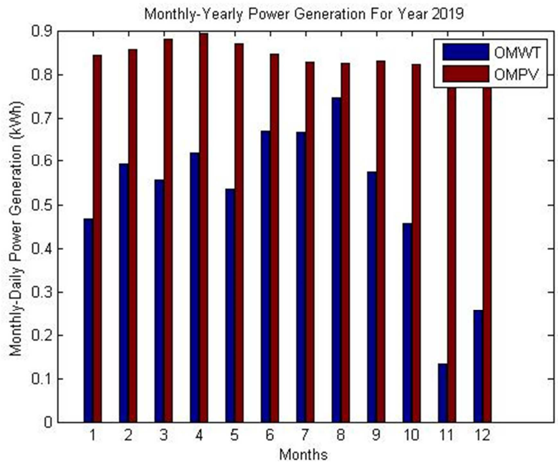

Figure 4. *Monthly-Daily Generation for 2019.*

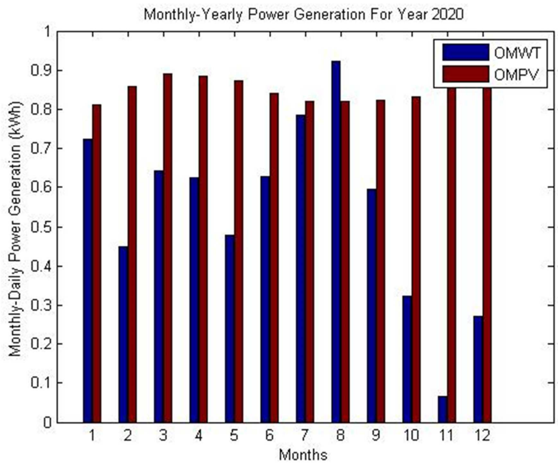

Figure 5. *Monthly-Daily Generation for 2020.*

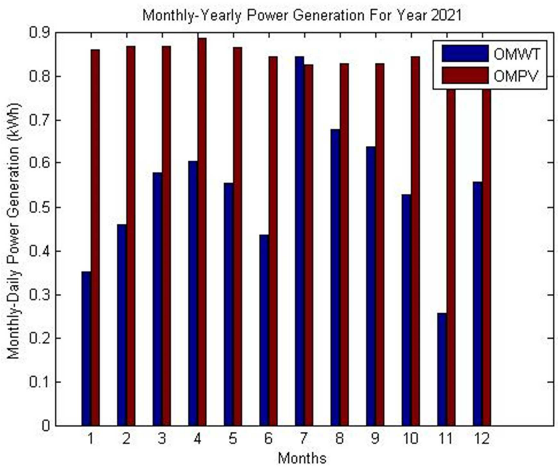

Figure 6. *Monthly-Daily Generation for 2021.*

4.4. AHREPS Simulations

The AHREPS simulations will highlight the monthly-daily generated RE power and will alternate among the OMPV and OMWT to supply the estimated load demand using the (model select criteria). Using the mode select critical based on greater than or less than the load demand, the AHREPS will select using the 0:1 ratio the chosen RE system needed to supply the estimated load demand.

Initial simulation experiments with the AHREPS program revealed that the Solar PV as the primary source will utilize 3 Solar PV modules of 200w connected in parallel in order to match the loading requirements and the Wind turbine to operate as support using the Hummer series H6.4-5KW WT generator. The model select states are as shown in Tables 8 through 11 for the years 2018 through 2021.

Table 8. *Model Select States (2018).*

Month (id)	OMWT mode	Pomwt (kW)	OMPV mode	Pompv (kW)
January (1)	0	0.38	1	0.89
February (2)	0	0.60	1	0.88
March (3)	0	0.68	1	0.87
April (4)	0	0.76	1	0.87
May (5)	0	0.65	1	0.86
June (6)	0	0.71	1	0.83
July (7)	0	0.69	1	0.83
August (8)	0	0.81	1	0.82
September (9)	0	0.52	1	0.83
October (10)	0	0.43	1	0.84
November (11)	0	0.12	1	0.87
December (12)	0	0.15	1	0.83

Table 9. *Model Select States (2019).*

Month (id)	OMWT mode	Pomwt (kW)	OMPV mode	Pompv (kW)
January (1)	0	0.47	1	0.84
February (2)	0	0.59	1	0.86
March (3)	0	0.56	1	0.88
April (4)	0	0.62	1	0.89
May (5)	0	0.53	1	0.87
June (6)	0	0.67	1	0.85
July (7)	0	0.67	1	0.83
August (8)	0	0.75	1	0.83
September (9)	0	0.57	1	0.83
October (10)	0	0.46	1	0.82
November (11)	0	0.13	1	0.86
December (12)	0	0.26	1	0.83

Table 10. *Model Select States (2020).*

Month (id)	OMWT mode	Pomwt (kW)	OMPV mode	Pompv (kW)
January (1)	0	0.72	1	0.81
February (2)	0	0.45	1	0.86
March (3)	0	0.64	1	0.89
April (4)	0	0.62	1	0.89
May (5)	0	0.48	1	0.87
June (6)	0	0.63	1	0.84
July (7)	0	0.79	1	0.82
August (8)	1	0.92	0	0.88
September (9)	0	0.60	1	0.82
October (10)	0	0.32	1	0.83
November (11)	0	0.07	1	0.86
December (12)	0	0.27	1	0.84

Table 11. *Model Select States (2021).*

Month (id)	OMWT mode	Pomwt (kW)	OMPV mode	Pompv (kW)
January (1)	0	0.35	1	0.86
February (2)	0	0.46	1	0.87
March (3)	0	0.58	1	0.87
April (4)	0	0.60	1	0.89
May (5)	0	0.55	1	0.86
June (6)	0	0.43	1	0.84
July (7)	1	0.94	0	0.83
August (8)	0	0.68	1	0.83
September (9)	0	0.64	1	0.83
October (10)	0	0.53	1	0.84
November (11)	0	0.26	1	0.86
December (12)	0	0.56	1	0.82

4.5. AHREPS Results

The results presented thus far indeed show the advantage of the data driven techniques in the solution process of alternating between a hybrid renewable energy system basing on the AHREPS model.

In particular, for the years 2020 and 2021 in Table 10 and Table 11, it is evident that any one of RE systems – OMWT or OMPV can either attain a 1 (selected) or 0 (non-selected) state but not both at same time. It is also evident that the AHREPS Binary Data Driven Programming (BDDP) solution generally shows that the AHREPS employed the OMPV RE system for the months of January through June and the months of September through December all through the 4-year duration (2018-2021) but in the months of July (2021) and August (2020), the AHREPS program employed the OMWT RE system in providing continuous power supply for the estimated load. This clearly shows that considering the model selection and alternating effects of the hybrid RE system, the proposed AHREPS model can effectively meet the estimated load demand of the aforementioned location.

5. Conclusions

The need to effectively determine the hybrid renewable energy (RE) requirements for any region is a dynamic situational estimation problem that requires the load demand and associated costs of RE system installations to be accounted for.

In this research study, an innovative attempt at implementing a useful estimating approach is proposed where the individual and alternating roles of a hybrid RE systems are taken into account.

The research conducted studies on the Otokwu-Mmaku Community, Awgu, Enugu State, Nigeria. From these studies, Geolocation data was obtained and used in the extraction of useful wind-solar data from the NASA National Renewable Energy (NRE) center.

This research explored the use of AHREPS logical simulation routine as a Binary Data Driven Programming (BDDP) solution in MATLAB language to evaluate the most likely RE system to be considered in a given year. The results showed that the AHREPS employed the OMPV RE system for the months of January through June and the months of September through December all through a 4-year duration (2018-2021) but in the months of July (2021) and August (2020), the AHREPS employed the OMWT RE system in providing continuous power supply for the estimated load.

For the case of meeting the expected load demand of at least 0.9kWh/day basing on the alternating role of the hybrid RE systems, the AHREPS simulation program showed that this is possible for the entire months of the year using a 3-parallel connected 200W Solar PV modules and 4-5kW Wind turbine generator.

Finally, the use of an effective but simple linear model of Solar Energy and Wind Energy distribution in a combined Binary Data Driven Programming (BDDP) solution for alternating between hybrid RE systems indeed shows that it can replace the traditional models of only one RE system.

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