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Hierarchical Power Scheduling Algorithm and Energy Management System in a Smart Solar Micro Grid

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Abstract: In recent years, as the development of the modern technologies in information, communication, control and computing, our living environment is becoming ”smart.” Smart Home and Smart City have gradually become part of our lives, and are no longer merely future concepts for the public. Microgrids have been set up to try and bring electricity to people even living in remote and rural areas. Even though different techniques have been applied to solve this problem, nevertheless there seems to be scarcity in deep exploration of local and indigenous solar power generation and weather data unique to the African context while dealing with this issue. In this dissertation, an optimal configuration algorithm for sharing energy resources in a microgrid using data collected from a microgrid located in Nigeria has been developed. The microgrid was divided into three (3) blocks (containing different offices) with different load distribution. The system was analyzed to determine the degree of deviation of the supplied power from the load demand. Results showed that in one of the blocks, the developed system showed a 89.2% improvement in the amount of surplus energy generated by the system. Simulation results also showed that the conventional system suffered the worst draw down during peak load demands. The battery SoC in block A went below the acceptable 30% threshold, while at that instance the SoC for the developed system in this work was about 57%. The developed worked showed about 27% improvement on the existing system even at peak load periods. Simulation results showed that as at 100 seconds, the error percentage of the existing design spiked to 7% while that of the developed algorithm was tending to zero. The system response when switching between different scenarios was also examined, and it was discovered that the developed algorithm responded to the switch in just 80mS.
Keywords: Microgrid, Solar PV, ELDI, Scheduling algorithm, Energy Management

I. INTRODUCTION

In Africa where most of the countries have extremely low electrification rates, microgrids have been set up to try and bring electricity to people living in villages. These microgrids utilise both conventional fuels and renewable resources. The majority are based on Solar PV deployed in areas that are isolated from the main grid. Due to insufficiency of transmission line capacity to attend with the increasing demand, more concern is growing towards distributed generators and microgrids.

Presently, seventy-six million Nigerians or 40.7% of the Nigerian population (more than twice the population of Canada) are not connected to the national power grid. For those connected, power supply is a serious problem as about approximately 90% of total power demanded is not supplied [1]. The problem is that even though Nigeria is endowed with large oil, gas, hydro and solar resources, and has the potential to generate about 12,522 MW (Which is the total installed generation capacity of electric power from existing plants); on most days, however, the average operational generation capacity is just 3,879MW of which 7.4% is lost in transmission, and up to 27.7% load is rejected at distribution. This leaves Nigeria with just about 2,519MW. Yet, Nigeria’s electricity demand was estimated at 24,380 MW in 2015 [1].

In recent years, as the development of the modern technologies in information, communication, control and computing, our living environment is becoming ”smart.” Smart Home and Smart City have gradually become part of our lives, and are no longer merely future concepts for the public [2]. An important component of Smart City is the Smart Grid (SG), which is regarded as the next generation power grid to create a widely distributed energy generation and delivery network. Smart grid technologies find application across the world. This ranges from isolated islands to very large integrated systems. In the developed world, smart grid technologies enable the upgrading and extension of existing grid systems, while providing opportunities for the incorporation of innovative solutions. In developing countries, smart grid technologies are essential to avoid lock-in of outdated energy infrastructure and attract new investment streams. This creates an efficient and flexible grid system that accommodates the rising electricity demand and a range of different power sources [2].

The traditional centralized form of energy generation in Nigeria has been found to be inadequate to meet the nation energy demands. This has made several energy consumers within the region to generate their own electricity. The problem here is that with distributed generation comes several issues like power quality assurance (from the several generating stations), balancing energy demand and supply, security, smart metering for tariff management, etc. Even though different techniques have been applied to solve this problem, nevertheless there seems to be scarcity in deep exploration of local and indigenous solar power generation and weather data unique to the African context while dealing with this issue. In this dissertation, an optimal configuration for sharing energy resources using data collected from a microgrid located in Nigeria is developed.
The aim of this paper is to model a hierarchical power scheduling algorithm and energy management system in a smart solar micro grid.

II. REVIEW OF RELATED LITERATURE

Smart grid (SG) technologies emerged from earlier attempts at using electronic control, metering, and monitoring. In the 1980s, automatic meter reading was used for monitoring loads from large customers, and evolved into the Advanced Metering Infrastructure of the 1990s, whose meters could store how electricity was used at different times of the day [3]. Smart grid (SG), also called smart power grid or intelligent grid, is regarded as the next generation power grid. It is supposed to replace the current old, dirty, inefficient, and vulnerable power grid. With modern technologies in power system, control theory, communication system, and information theory, two-way flows of electricity and information will be enabled in SG to provide an advanced power system with higher energy efficiency and power delivery stability. Microgrid is another emerging paradigm in SG, which is a small power grid composed of localized medium or low level power generation, energy storage, and loads. The microgrid can be seen as the building block of smart grids. It comprises low voltage (LV) system with distributed energy resources (DERs) together with storage devices and flexible loads. The DERs such as micro-turbines such as, fuel cells, wind generator, photovoltaic (PV) and storage devices such as flywheels, energy capacitor and batteries are used in a microgrid [2]. The authors of [4] presented a hierarchical two-layer home energy management system to reduce daily household energy costs and maximize photovoltaic self-consumption. According to [5], the Rapid growth of data in smart grids provides great potentials for the utility to discover knowledge of demand side and design proper demand side management schemes to optimize the grid operation. [6] proposed an ameliorated hybrid solar and wind accompanied by a battery management system with specialized and accurate controllers developed using the PID controller. The paper by [7] presents an analytical framework to develop a hierarchical energy management system (EMS) for energy sharing among neighbouring households in residential microgrids. [8] did a comprehensive literature review on the applications of predictive control in microgrids.
With the gradual adoption of microgrids, there have been a number of surveys investigating the state of the art as well as identifying challenges and future research directions. Some of the reviewed works investigated energy management systems in microgrids – their functionalities, architecture, control philosophies, and existing software. From the indepth review done, there exist adequate literatures that looked at the modeling, planning, and energy management of microgrids with cooling, heating, and power cogeneration capabilities. Even though different techniques have been applied to solve this problem, nevertheless there seems to be scarcity in deep exploration of local and indigenous solar power generation and weather data unique to the African context while dealing with this issue. In this paper, an optimal configuration algorithm for sharing energy resources in a microgrid using data collected from a microgrid located in Nigeria has been developed.

III.SYSTEM MODEL

The methodology employed in this work involved the characterization of the test bed, sizing of the test bed, and data collection from the test bed to enable the accurate development of the algorithm. The testbed is located at Electronic Development Institute (ELDI), Km 80 Enugu-Onitsha Expressway Awka Capital Territory, Abba Junction, P.M.B, 5099, Awka. ELDI is a Research Institute under National Agency for Science and Engineering Infrastructure. Abba is one of the communities in the present-day Njikoka Local Government Area of Anambra State, Nigeria. Abba lies on the 60 11′ N latitude, 60 55′ E longitude of the old Enugu/Onitsha trunk ‘A’ road through the local government headquarters, Abagana. The region in general has hot climate throughout the year with slight difference between summer and winter. The climate is usually characterized into 2 seasons – the Wet and Dry. The wet season (summer) is normally from April to October while the dry season (winter) is from November to March. By climatic regions, it features a tropical rainforest climate with yearly rainfall of 60-80 inches a year. ELDI occupies about 35,000 square meters, and is encompassed with buildings sparsely located with also a great portion of unused land. The aerial view is as shown in figure 1.

Figure 1: Aerial view of ELDI

The microgrid developed by ELDI's was aimed at integrating renewable energy sources (mainly solar) with both grid and DG facility. The system modeled in this work is a power distribution system in the microgrid environment with a certain number of sources, consisting of solar PV plants, storage batteries, generator set, and utility. The system contains an Energy Management System (EMS) that is responsible for coordination of all components of the microgrid. In this work, different scenarios are employed to effectively maximize the microgrid operations. The main function of the EMS is to optimally schedule the different sources of the microgrid based on the selected scenario for each hour in order to minimize the operating cost of the microgrid under some constraints. The graphical illustration of the EMS is as shown in figure 2.

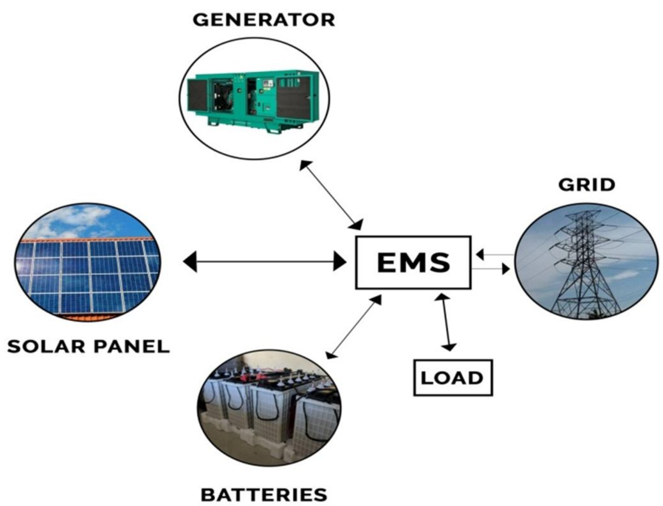

Figure 2: EMS

The algorithm developed in this work was designed to run on the EMS and would enable the efficient scheduling of the energy resources in the microgrid. The following scenarios were considered:

1) *Scenario 1:* In this scenario there is no power that can be transferred from the utility or the main grid. Thus, the microgrid operates in islanded mode, depending only on solar power supply
2) *Scenario 2:* All DGs can work within their limits and the microgrid can buy limited power from the utility only when DGs cannot supply the requested load.
3) *Scenario 3:* The microgrid has the facility of storage batteries and all DGs can work within their limits. As shown in figure 3.5, it is pertinent that if the generated power from DGs is greater than the load, the surplus energy is used to charge the battery bank. In the case where the battery bank is fully charged, no extra power will be generated from the DGs. On the other hand, if the power generated by DGs is less than the requested load, the deficit of power is provided by the battery bank. If DGs and the battery bank cannot supply the load, the deficit of power is bought from the main grid.
4) *Scenario 4:* In this scenario, the microgrid depends solely on generator set supply only when solar supply, battery storage and utility is unavailable.

The role of the EMS is to minimize the load variance in the microgrid and optimally schedule the different sources of the microgrid based on the selected scenario for each hour in order to minimize the operating cost of the microgrid under some constraints. This is formulated mathematically as an optimization problem whose objective function is approximated by a quadratic nonlinear function as follows:

$$C_i(t) = \propto_i \times P_1(t)^2 + \beta_i \times P_i(t) + \gamma_i \quad (1)$$

Where $\propto > 0$ and $\beta, \gamma \geq 0$ are pre-selected for the power grid. Also i denotes the number of DG units under consideration, C and P represent the cost in $ and power generated in MW on an hourly basis, respectively. DG technology and fuel cost are incorporated in coefficients $\propto$, β, and γ, where $\propto$ specifically, is used to introduce DG related nonlinearity.

The system is assumed to meet the user demand under an acceptable cost constraint $c(t)$ at time t, which is not expected to exceed the constraint:

$$C_i(t) \leq c(t), \forall \, t \in \{1,2, \ldots, T\} \quad (2)$$

The cost constraint $c(t)$ is referred to as the budget, and without loss of generality, it is assumed that $c(t)$ is an ergodic process, which is taken from a set $\mathbb{C}$, i.e., $c(t) \in ₵$. Where ₵ is the set of maximum cost for the energy provider at any time t.

The power consumption of each user i at time t is denoted as $p_i(t)$ and at each time slot, user i's minimum demand $p_{i\,min}(t)$ is expected to meet the following condition: $p_i(t) \geq p_{i\,min}(t), \forall \, i \in \mathbb{N}, t$. where $\mathbb{N}$ is the set of electricity users in the system.

The system also assumes that the users are rational, which means that at each time slot, the power demand of each user has an upper bound, i.e., $p_i(t) \leq p_{i\,min}(t)$. Though this will not become a constraint in the problem, because the algorithm is designed to satisfy the user demand as much as possible under other constraints. However, this assumption along with equation (1) guarantees a closed set $\mathbb{P}$ which includes all the possible value of power demanded and used, that is, $p_i(t) \in \mathbb{P}$. The algorithm also assumes independent users with their own preferences of power usage. Thus each user could have its own time schedule for using different electrical appliances. Also, the user demand may vary as weather changes.

The algorithm also ensures that the power produced by the EMS must be equal to the requested load at any instant. This is represented by the constraint:

$$\sum_{i=1}^{\mathbb{N}} P_i(t) + P_{Battery}(t) + P_{Grid}(t) = P_L(t) \quad (3)$$

Where $P_L(t)$ is the total power required by the load at any instant t, $P_{Battery}(t)$ is the power of storage batteries, and $P_{Grid}(t)$ is the power from the grid at instant t. It is worth to mention that, $P_{Battery}(t)$ and $P_{Grid}(t)$ depend on the selected scenario.

The batteries are considered as a secondary source of power, and can charge and discharge within a given range. the algorithm's objective is to keep the SOC consistently in the 30% to 80% charge range to ensure that the batteries do not reach extremely high or low ranges. The algorithm will monitor the SOC. If the SOC passes either the upper or lower limit, the power supplied by the main grid will be adjusted to ensure that SOC stays within the established ranges. The logic of the algorithm is to check the SOC every two hours and adjust the system accordingly. The following actions of adjustments are taken based on the detected conditions

The constraint is posed as:

$$P_{Discharge\,min}(t) \leq P_{Battery}(t) \leq P_{Charge\,max}(t) \quad (4)$$

Where $P_{Discharge\,min}(t)$ is the minimum discharging value allowed for the batteries at time (t) and $P_{Charge\,max}(t)$ is the maximum charging capacity of the batteries.

The optimization problem is then posed as follows:

$$minimize \; C_i(t) = \propto_i \times P_1(t)^2 + \beta_i \times P_i(t) + \gamma_i \quad (5)$$

$$subject\ to \begin{cases} C_i(t) \leq c(t), \forall \, t \in \{1,2, \ldots T\}, c(t) \in ₵ \\ p_i(t) \geq p_{i\,min}(t), \forall \, i \in \mathbb{N}, t, \; p_i(t) \in \mathbb{P} \\ \sum_{i=1}^{\mathbb{N}} P_i(t) + P_{Battery}(t) + P_{Grid}(t) = P_L(t) \\ P_{Discharge\,min}(t) \leq P_{Battery}(t) \leq P_{Charge\,max}(t) \\ \propto > 0, \beta, \gamma \geq 0 \end{cases}$$

The goal of the mathematical optimization is to determine a set of values $C_i(t)$ that provides the minimum value of the objective function f, while at the same time satisfying the set of constraints. The optimization problem would be solved using Lagrange method. Matlab codes are written in appendix E to solve this problem. The online algorithm is as follows:

1) *Step 1:* For each $i \in N$, initialize $p_i(t) \in \mathbb{P}$.
2) *Step 2:* In each time slot t, the DCC solves the following optimization problem

$$minimize\ C_i(t) = \propto_i \times P_1(t)^2 + \beta_i \times P_i(t) + \gamma_i$$

$$subject\ to \begin{cases} C_i(t) \leq c(t), \forall\, \mathrm{t} \in \{1,2, \ldots \mathrm{T}\}, \mathrm{c}(t) \in ₵ \\ p_i(t) \geq p_{i\,min}(t), \forall\, i \in \mathbb{N}, t,\ p_i(t) \in \mathbb{P} \\ \sum_{i=1}^{\mathbb{N}} P_i(t) + P_{Battery}(t) + P_{Grid}(t) = P_L(t) \\ P_{Discharge\ min}(t) \leq P_{Battery}(t) \leq P_{Charge\ max}(t) \\ \propto > 0, \beta, \gamma \geq 0 \end{cases}$$

Let $C_t^*(t)$ denote the solution to the problem, where each element $C_t^*(t)$ represents the optimal cost allocation to user i.

3) *Step 3:* Obtain $C_t^*(t)$ from step 2 and update $p_i(t)$for all $i \in N$.

The flow chart of the algorithm is as shown in figure 3:

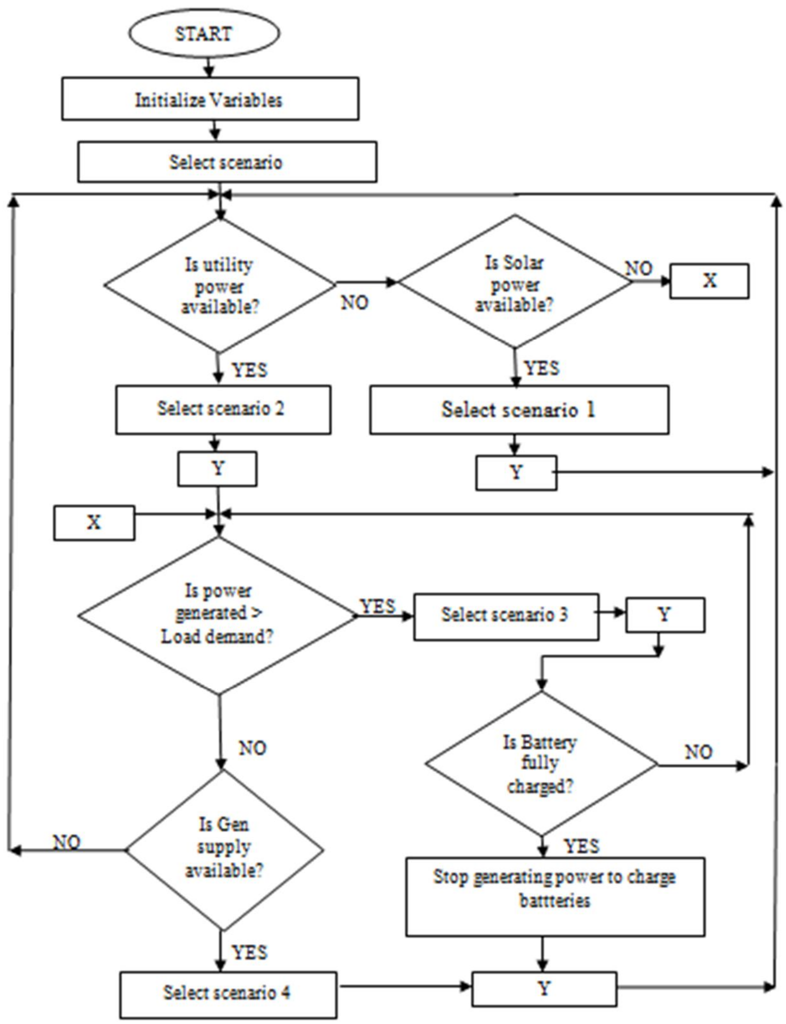

Figure 3: Flow chart of the algorithm

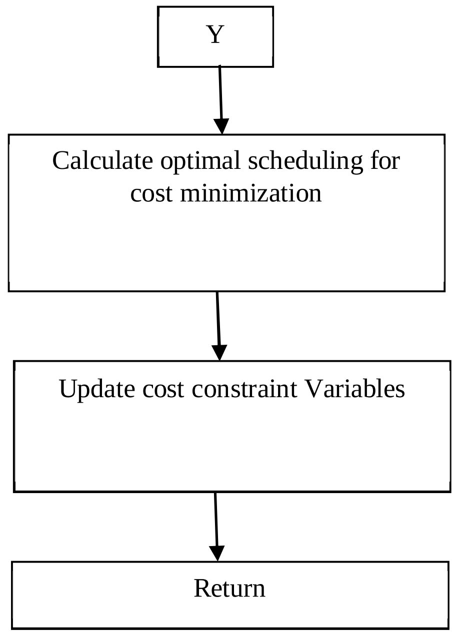

Figure 4: Flow chart of the algorithm

To solve the optimization problem, system sizing was carried out on the test bed being modeled. This would enable the algorithm to acquire parameters that are tailored to meet real life demands.
System sizing is a very critical step in the design of microgrids. This enables creation of load profiles that show the trend of electricity consumption as a function of time usually over a full day. Even though the testbed sizing had already been done by the original designers of the microgrid, it is important that another sizing is done in this work. This is because the author cannot account for the accuracy of the original sizing. It is important to note that poor load estimation leads to undersizing/oversizing of the system. This in turn leads to a less reliable system or one that is very costly. Accurate modelling enables us to create load profiles that show the trend of electricity consumption as a function of time. It helps to represent the quantity of energy in Watthours (Wh) that the particular users require in a given day.

Three main steps must be followed to calculate the proper size of a photovoltaic system

1) *Estimate The Required Electrical Energy (The Demand):* A load profile is developed by recording the power consumption of the equipment as well as the estimated usage time. Then the electrical energy required on a monthly basis is calculated. In doing this, consideration is made of the expected usage fluctuations due to variations between the rainy and dry season, school and vacation periods, etc. The result will be 12 energy demand values, one for each month of the year. The power consumption also includes the inverter efficiency in the case of DC-AC conversion.
2) *Determine The Available Solar Energy (The Resource):* Hourly Solar Resource Data is required to determine Solar PV production during 24-hours Load Cycle. Awka which is 6.210528 and the longitude is 7.072277. The study choice software used to obtain this data is the Hybrid Optimization of Multiple Electric Renewable (HOMER) software. HOMER is a performance and financial model designed to facilitate decision making for researchers Involved in Renewable Energy Industry. For the study, Weather Data File for Awka was obtained through its co-ordinates (Longitude and Latitude) using HOMER Platform. Hour-by-Hour Solar Resources was used to calculate solar PV power output consisting of hourly values of Solar resources for some time. Monthly Solar Resource Data were selected randomly to reduce errors due to climatic uncertainty of the year. Solar energy data is usually stated in monthly intervals, reducing the statistical data to 12 values. This estimation is a good compromise between precision and simplicity.
3) *Combine Energy Demand And Energy Offer (The Matching):* To determine that ratio the research divided the energy demand by the energy resource (peak sun hours). The month with the highest resulting figure is the month with the least favorable relation between energy demand and availability. Solar energy and energy demand data from that month was used to size the photovoltaic system. Solar irradiation data for the Abba Town Ngikoka LGA in Awka Capital City Anambra state in Nigeria was used. Using solar energy data and energy demand data for that particular month the following was calculated:

a) Necessary energy storage capacity of the battery bank
b) Energy generation capacity of the solar array
c) Size, number and type of solar panels
d) Required electrical characteristics of the regulator
e) Length and diameter of cables required for electrical connections

The microgrid is divided into three (3) blocks (containing different offices) with different load distribution. Tables 1 contains the summazied data calculated for the microgrid.

TABLE I
DATA FOR ALL THE BLOCKS

Variable	Block A	Block B	Block C
Total appliance Energy $E_{c\,(Vah)}$	1055192.28	264618.63	28777
Consumer Energy Demand E_{cd}(Vah)	1140622.25	288144.86	31249
Total Appliances Power P_o (VA)	124556.38	39995.54	39879.
Inverter Power Rating P_{inv}(KVA)	166	54	54
Battery Discharge D_B (Ah)	4752.59	2401.21	2604.
Battery Capacity C_B (Ah)	28515.56	14407.24	1562
Battery needed N_T	2860	720	790
Total P_v current I_p (A)	1210.85	611.77	633.47
Panels Needed N_{TC}	1540	390	405
S_{cc} Needed N_{TC}	146	75	80
Cable size A(mm^2)	60	61	63

IV. RESULTS AND ANALYSIS

In this paper, the microgrid in consideration was modeled using the commercially available Homer software so as to enable the efficient comparison of the obtained results with the proposed sizing approach. The Homer software was chosen because of its rich feature list and ease of use. The Homer software package is owned by HOMER Energy in the United States of America and allows for modelling, sizing and simulation of microgrids with various energy sources. It can be used to simulate and analyse both standalone and grid-connected microgrid systems. It also has the capability to assess the performance, reliability and costs of the microgrid model. A simplified architecture of the HOMER software is shown in figure 5.

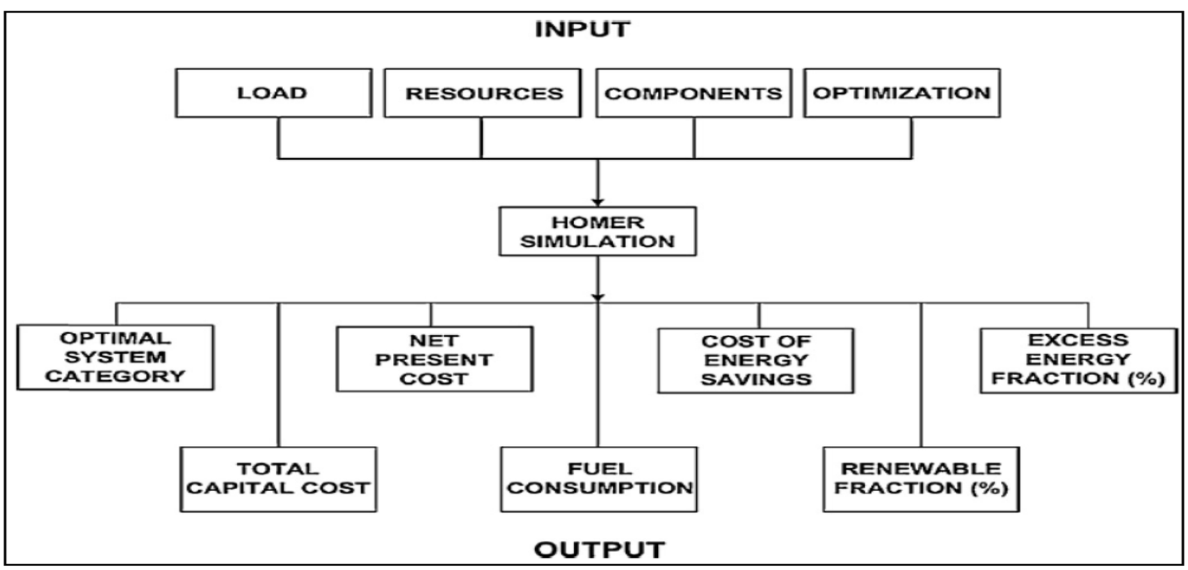

Figure 5: Architecture of HOMER software

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The Graphical User Interface (GUI) of the HOMER software is as shown in figure 6.

Figure 6: GUI of HOMER software

To enable the effective comparison with the testbed at ELDI, the sizing approach ensured that the specifications of each of the equipments were set to same value. Due to the intermittency of renewable energy sources, the power output from PV plants is irregular. Also the power from the grid is also irregular. The two stable sources available are Generator set and battery supply. The generator set operation is highly dependent on availability of diesel. The power from the battery bank is dependent on whether its charged or not. The simulation parameters are contained in table 2.

TABLE III
DATA FOR ALL THE BLOCKS

Parameter	Description
Batteries	Luminous (12V/200AH)
Solar Panel	300A
Run time	50 minute
Client grid size	35,000 Sq M
Population size	1000
Load Profile	Distributed

The load consumption of the various buildings in ELDI was plotted for a period of twenty four hours and twenty eight days of the month. The average daily power consumption for each month was taken into consideration and the daily power consumption was plotted. The various changes in weather as regards to west Africa was also taken into consideration. Using the information gotten from consumer usage pattern in the microgrid, the month of April was selected as having the highest power demand, and August as having the lowest power demand. The average use per hour for these months was sampled for each block and was presented as shown from figure 7 to 12.

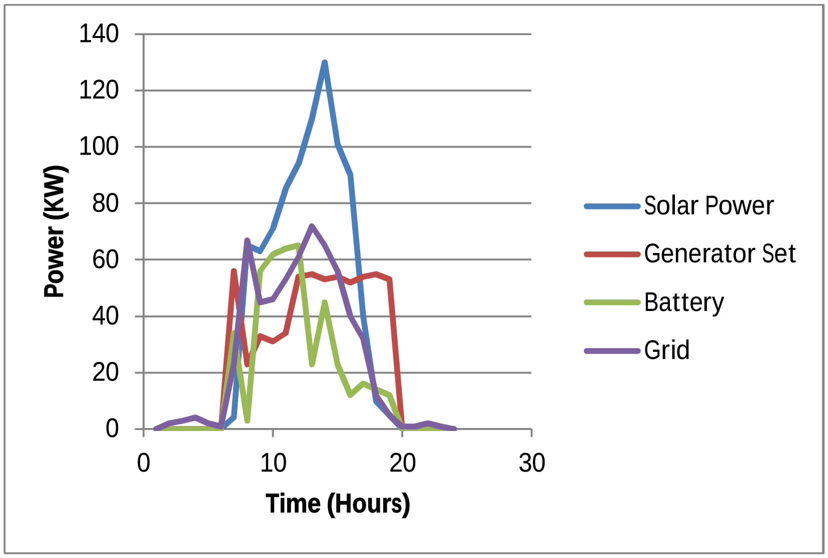

Figure 7 Average Power demanded from each DG per hour in a running day for April for Block A

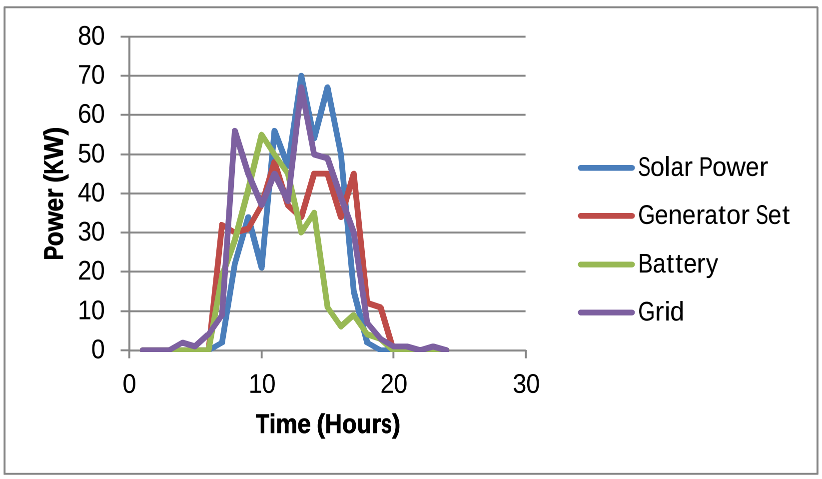

Figure 8 Average Power demanded from each DG per hour in a running day for August for Block A

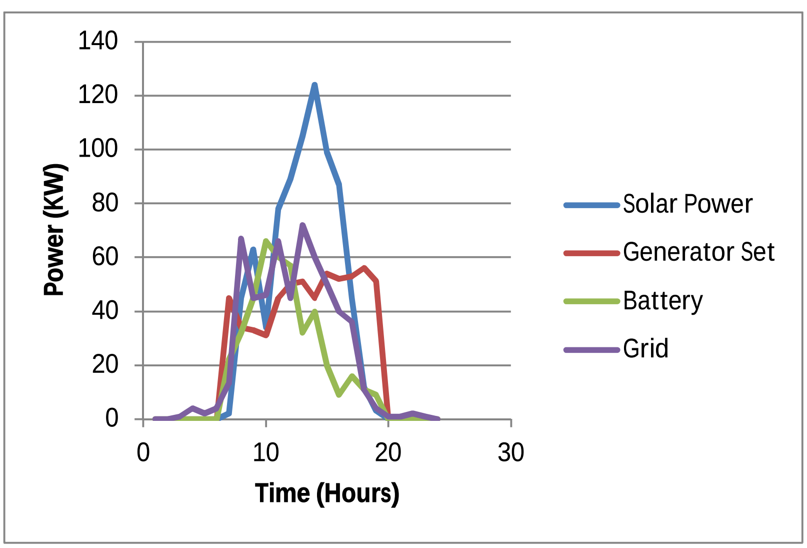

Figure 9 Average Power demanded from each DG per hour in a running day in April for Block B

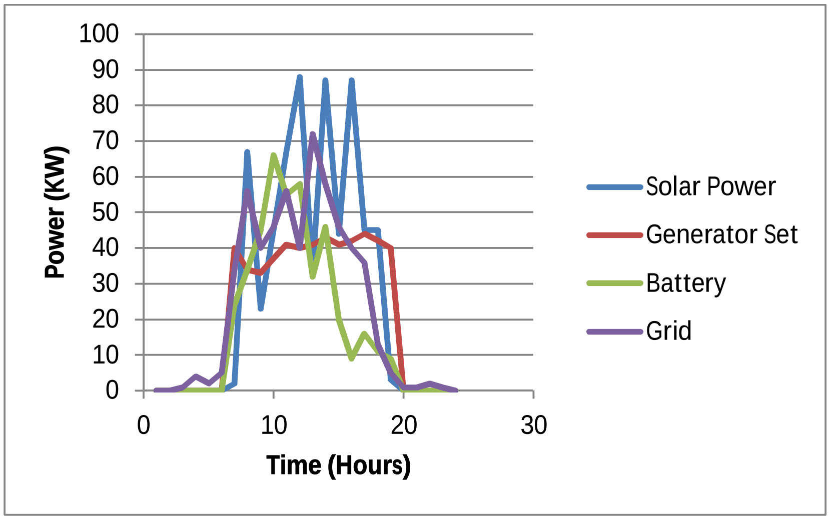

Figure 10 Average Power demanded from each DG per hour in a running day in August for Block B

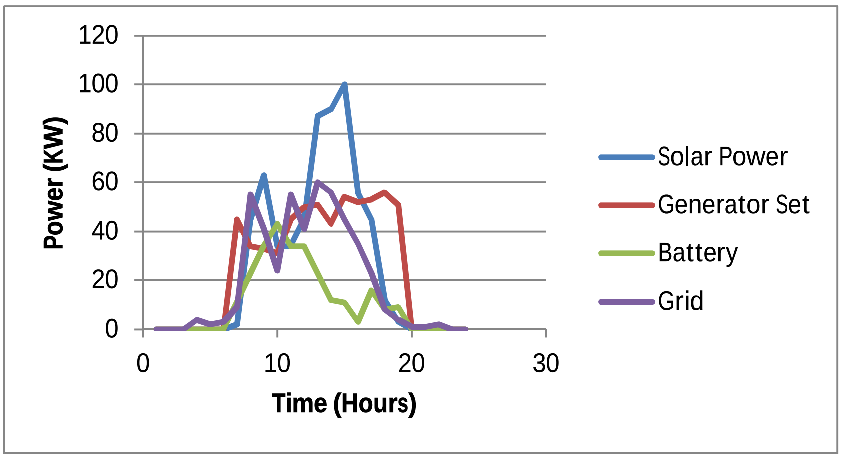

Figure 11 Average Power demanded from each DG per hour in a running day in April for Block C

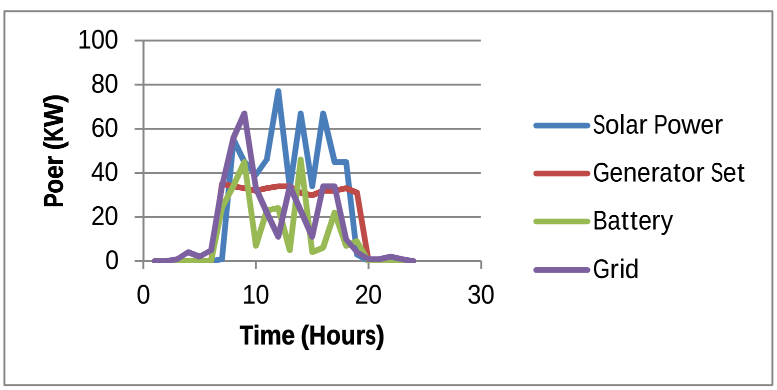

Figure 12 Average Power demanded from each DG per hour in a running day in August for Block C

From figure 7 to 12, it could be established that the peak hour usage of the system lies between 11AM and 3PM. This can be attributed to the amount of people making use of electrical appliances at those times. This evaluation helped to pre-inform the algorithm of times frames that preferences should be given to during resource allocation. One common problem identified in the test bed was that the existing batteries were frequently being replaced because they were packing up quickly. To address this issue in the current design, the performance of the batteries installed in the microgrid analyzed to see the impact on the SoC when compared to the exisiting system. This comparison is shown in figure 13 to 15.

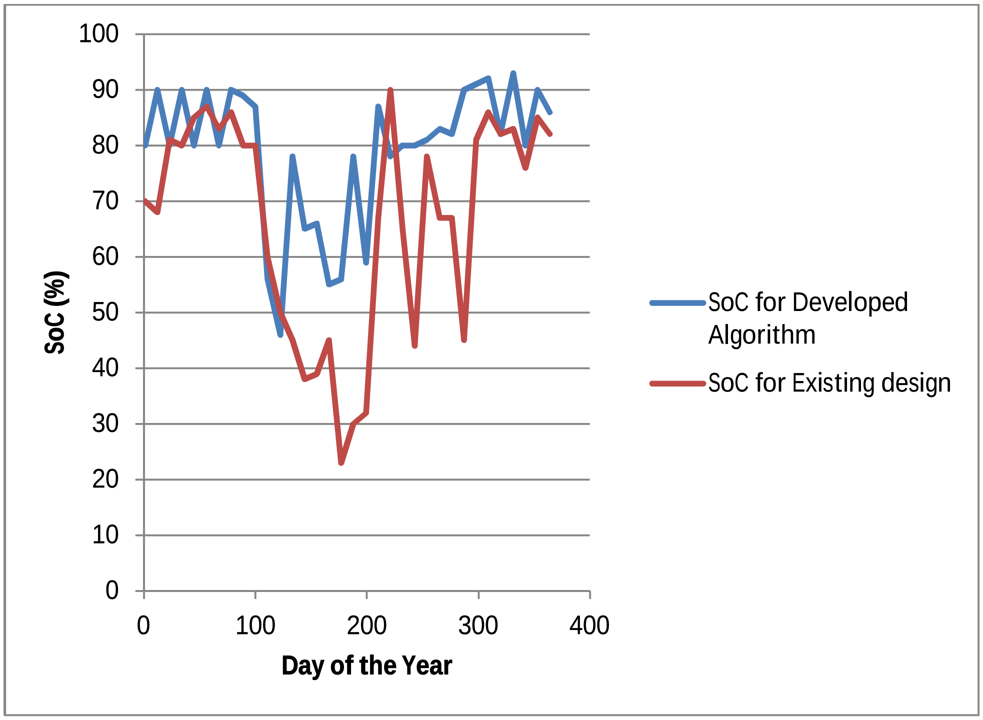

Figure 13: Average Daily Battery State of Charge When Using the developed algorithm and when using the existing design for block A

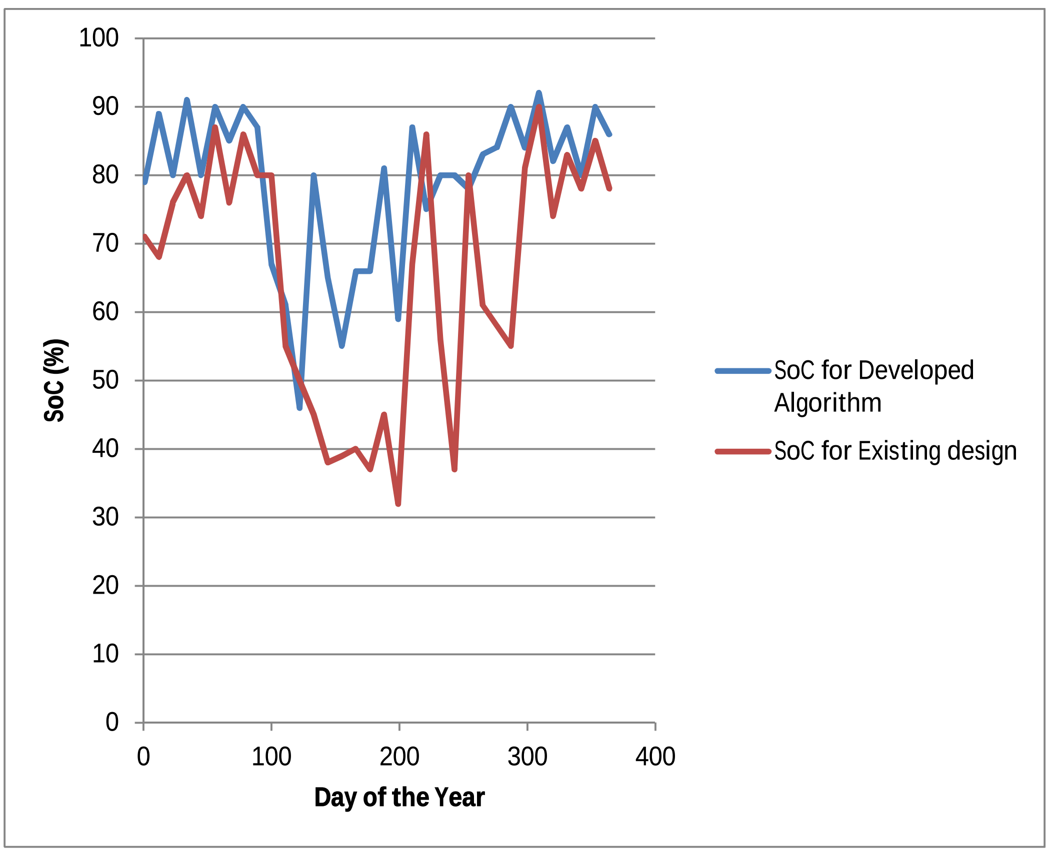

Figure 14: Average Daily Battery State of Charge When Using the developed algorithm and when using the existing design for block B

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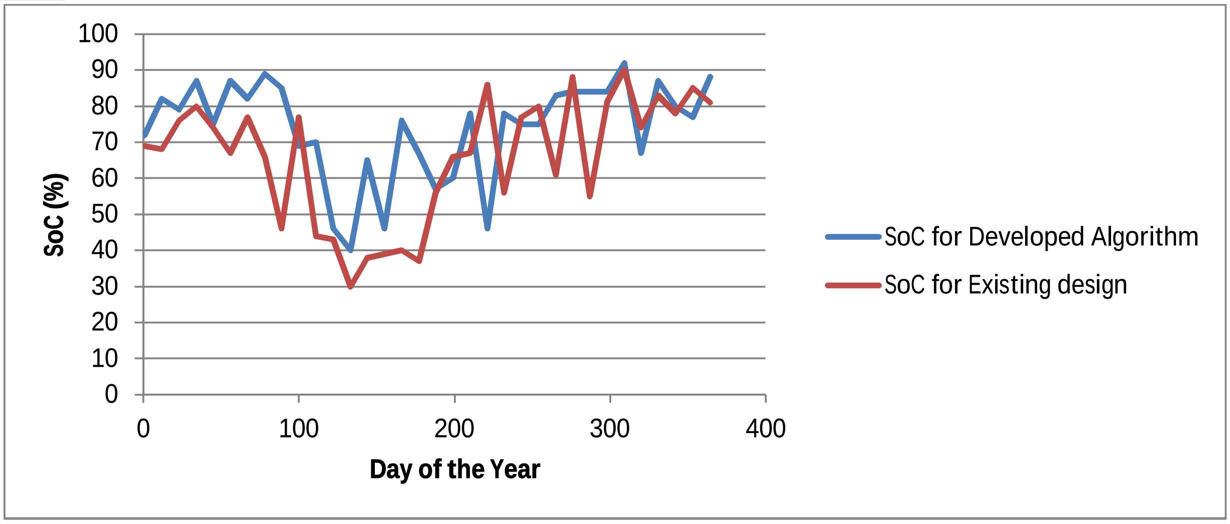

Figure 15: Average Daily Battery State of Charge When Using the developed algorithm and when using the existing design for block C

From the sizing done in this work, the number of batteries differ from the amount already installed in the existing design. The difference is due to the differences in the calculated quantities of Battery. Results obtained shows that the incorrect sizing and allocation of batteries in the existing design was responsible for the frequent packing up of the installed batteries. The impact of this sizing alongside the scheduling algorithm can be seen in how the system effectively manages the battery SoC even during adverse conditions. The SoC for the developed algorithm was always maintained within the range of 40% to 90%. For days of the year were the user demands in the blocks were at its peak, the system always ensured that the draw down on the battery was always within the acceptable range, else the demand is pushed to another energy source by the EMS. The conventional system suffered the worst draw down during peak load demands. Results showed that the battery SoC in block A went below the acceptable 30% threshold, while at that instance the SoC for the developed system in this work was about 57%. The developed worked showed about 27% improvement on the existing system even at peak load periods. The developed system experienced the worst draw down in block C. The lowest value of SoC mainted by system for the yeat was 40%. Even at this instance, the developed system showed a 10% improvement to the existing design.

Another major concern noticed in the existing system was the consistent shortage and inadequate supply of power to efficiently meet consumer's demands. To address this issue in the design carried out in this work, the software required that the following input requirements such as hourly irradiance, Simulations were done to carry out a comparison between the surplus energy and the deficit energy when the EMS was controlled by the developed algorithm and when it was running on the existing algorithm.

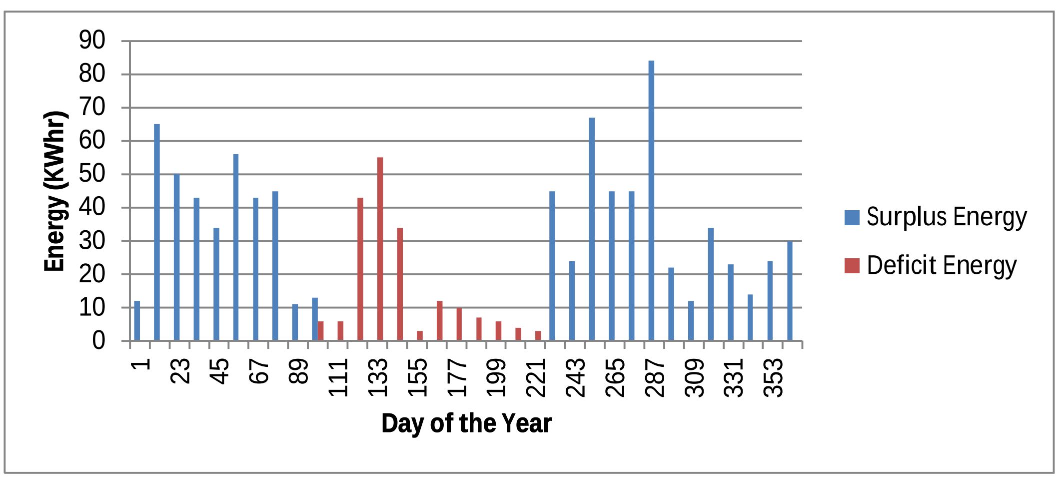

Figure 16: Average Daily Deficit Energy and Surplus Energy Throughout the Year for block A when using the developed algorithm

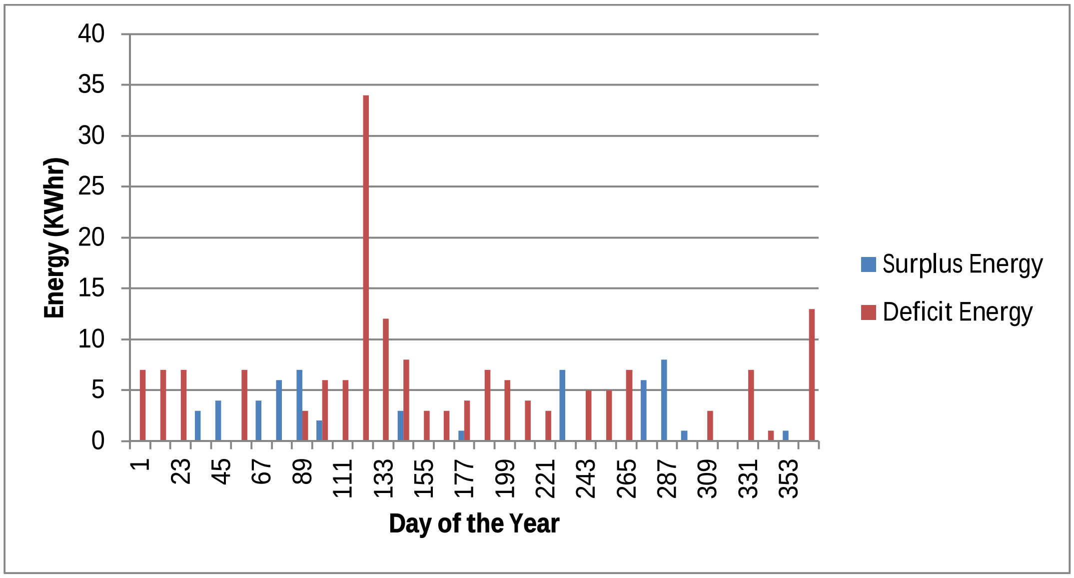

Figure 17: Average Daily Deficit Energy and Surplus Energy Throughout the Year for block A when using the existing algorithm

From the result obtained from block A as shown in figure 16 and 17, when the EMS was controlled by the developed algorithm, the total surplus energy generated in that block was 389KWhr, while the total deficit energy obtained was 114KWhr. In contrast, the existing system had a deficit of about 168KWhr and a surplus of about 56KWhr. Thus developed system showed a 56.8% improvement in the amount of surplus energy generated by the system. The advantage of this factor is that, the microgrid can afford to sell the surplus energy to the grid and thus generate revenue. Due to peak energy demand, there are always instances where the generated energy from any of the sources being depended upon might not be enough to service the load demand. At this instance, there is a energy deficit, which must be serviced by seeking for alternative sources, or applying load shedding. The developed system also showed a better performance even in terms of amount of deficit energy. The developed system had deficit energy of about 31.2% lower than the existing design.

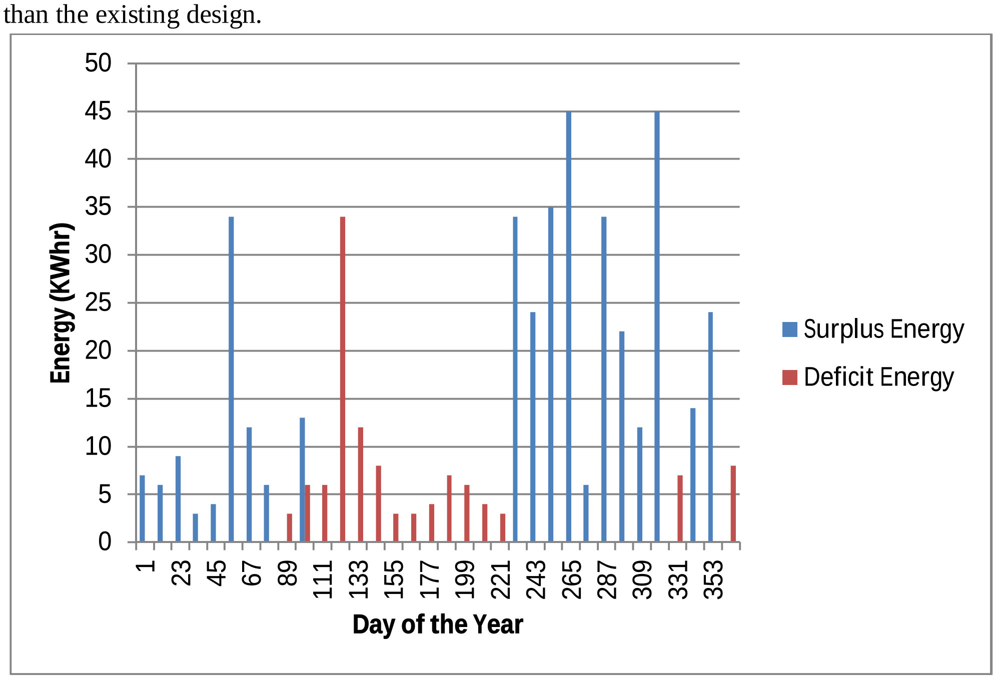

Figure 18: Average Daily Deficit Energy and Surplus Energy throughout the Year for Block B when using the developed algorithm

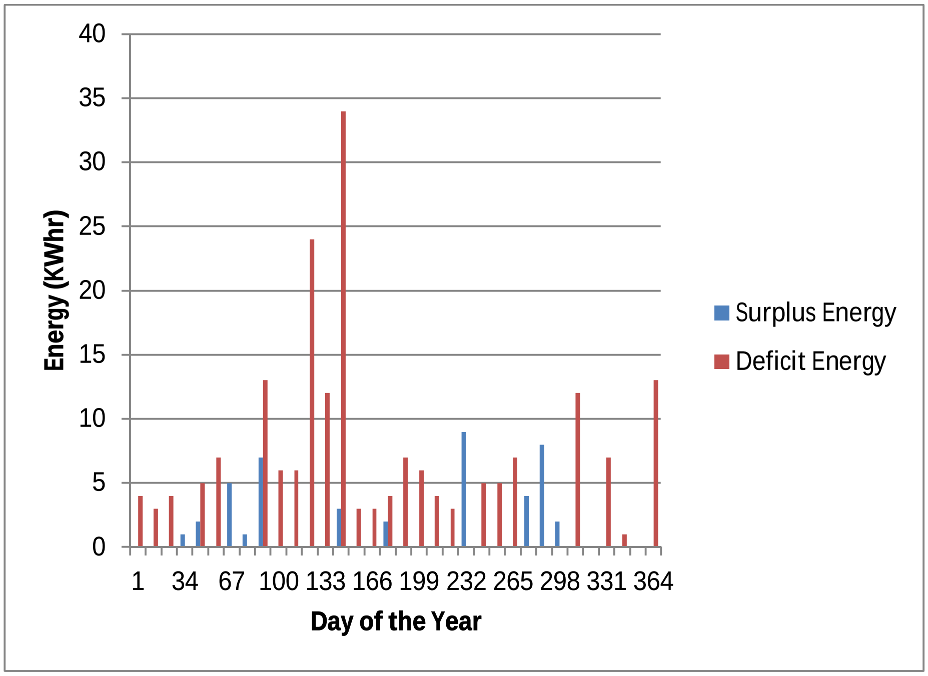

Figure 19: Average Daily Deficit Energy and Surplus Energy throughout the Year for Block B when using the existing algorithm

From the result obtained from block B as shown in figure 18 and 19, when the EMS was controlled by the developed algorithm, the total surplus energy generated in that block was 409KWhr, while the total deficit energy obtained was 106KWhr. In contrast, the existing system had a deficit of about 198KWhr and a surplus of about 44KWhr. Thus developed system showed a 89.2% improvement in the amount of surplus energy generated by the system. The developed system also showed a better performance even in terms of amount of deficit energy. The developed system had deficit energy of about 46.5% lower than the existing design.

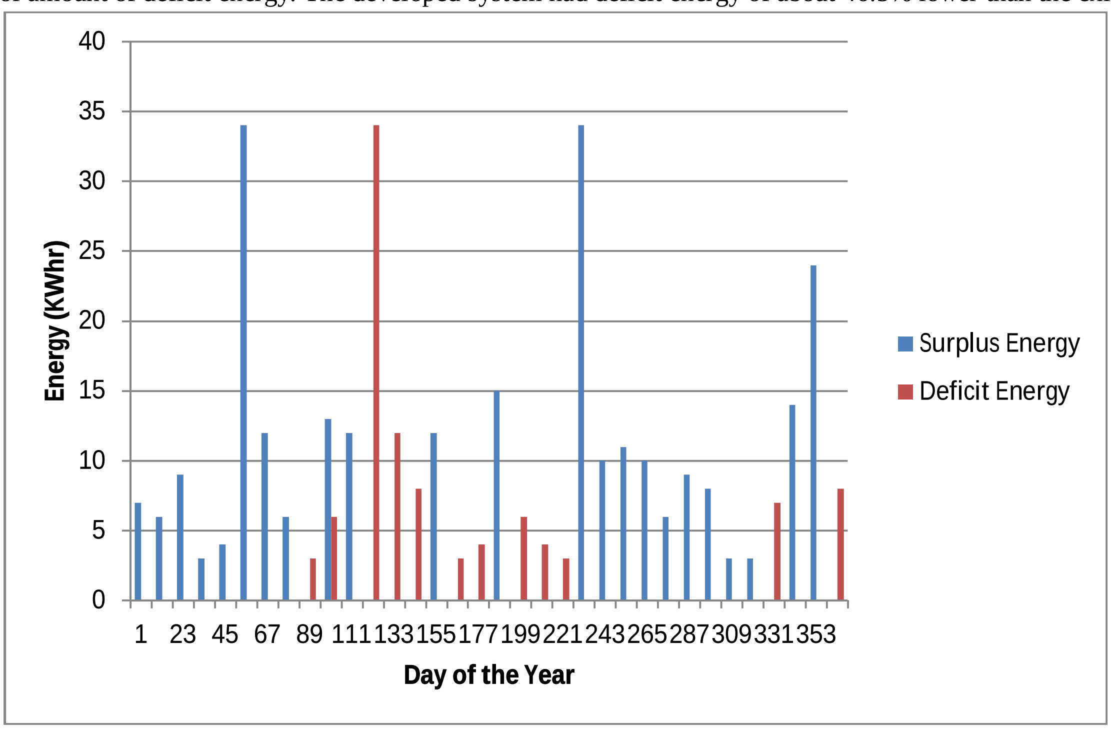

Figure 20: Average Daily Deficit Energy and Surplus Energy throughout the Year for Block C when using the developed algorithm

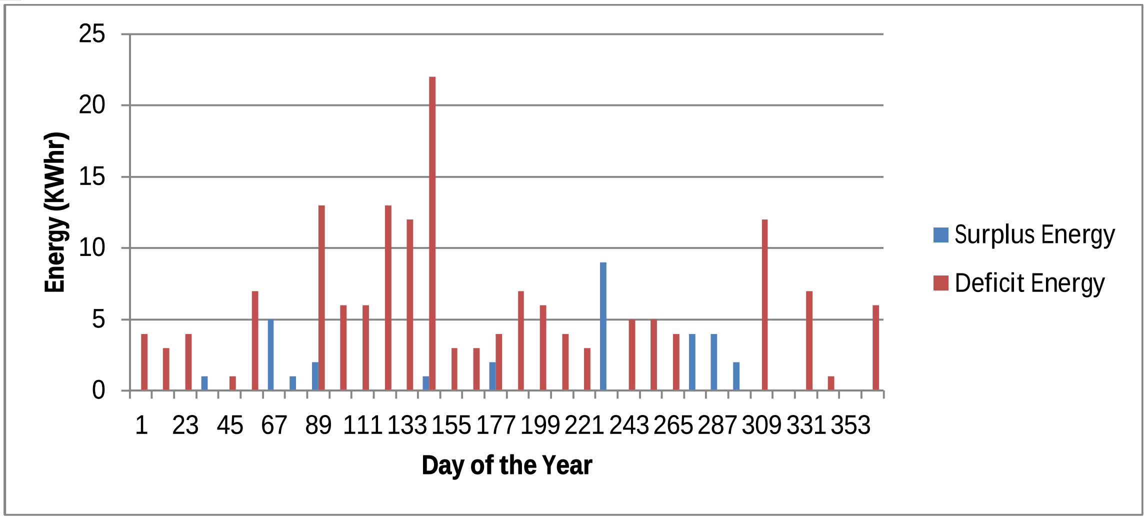

Figure 21: Average Daily Deficit Energy and Surplus Energy throughout the Year for Block C when using the existing algorithm

From the result obtained from block B as shown in figure 20 and 21, when the EMS was controlled by the developed algorithm, the total surplus energy generated in that block was 265KWhr, while the total deficit energy obtained was 98KWhr. In contrast, the existing system had a deficit of about 161KWhr and a surplus of about 31KWhr. Thus the developed system showed a 88.3% improvement in the amount of surplus energy generated by the system. The developed system also showed a better performance even in terms of amount of deficit energy. The developed system had deficit energy of about 39.1% lower than the existing design.

Using the constraints posed initially to find the optimum cost of the system operation, the system response to a change in scenario was plotted. This was to discover how fast the system responds to changes made to the EMS by the algorithm. The plot is as shown in figure 22.

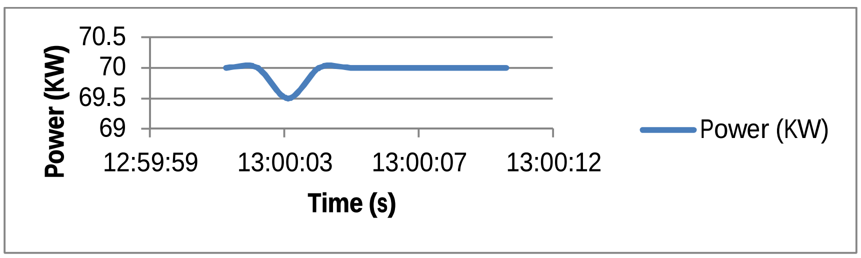

Figure 22: System response to a switch in scenario

From the diagram, it can be seen that the system responded to the switch in just 80mS. This goes to reveal that the algorithm does not lag at responses.

V. CONCLUSIONS

Several approaches (e.g., exact, stochastic, and predictive) have been proposed for energy management. Even though different techniques have been applied to solve this problem, nevertheless there seems to be scarcity in deep exploration of local and indigenous solar power generation and weather data unique to the African context while dealing with this issue. In this dissertation, an optimal configuration algorithm for sharing energy resources in a microgrid using data collected from a microgrid located in Nigeria has been developed. The microgrid was divided into three (3) blocks (containing different offices) with different load distribution.The system was analyzed to determine the degree of deviation of the supplied power from the load demand. Results showed that in one of the blocks, the developed system showed a 89.2% improvement in the amount of surplus energy generated by the system. Simulation results also showed that the conventional system suffered the worst draw down during peak load demands. The battery SoC in block A went below the acceptable 30% threshold, while at that instance the SoC for the developed system in this work was about 57%. The developed worked showed about 27% improvement on the existing system even at peak load periods. Simulation results showed that as at 100 seconds, the error percentage of the existing design spiked to 7% while that of the developed algorithm was tending to zero. The system response when switching between different scenarios was also examined, and it was discovered that the developed algorithm responded to the switch in just 80mS.

VI. ACKNOWLEDGMENT

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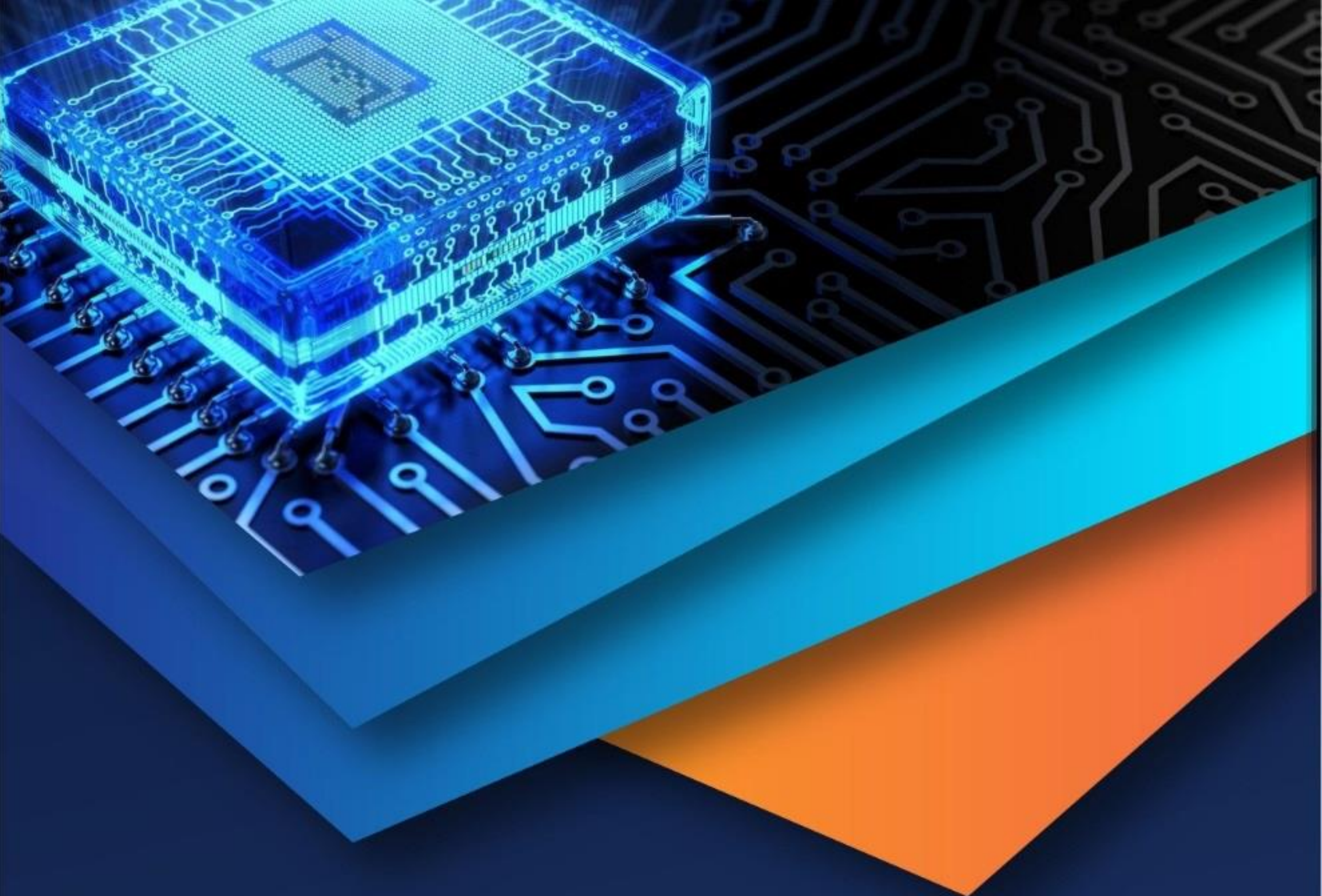

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