Towards A Micro Grid Based Residential Home Energy Management Using Genetic Algorithm

Norbert Uche Aningo
Leeds Sustainability Institute, School of Built environment, Engineering and Computing, Leeds Beckett University
Leeds, United Kingdom
Uchereal2010@yahoo.com

David Glew
Leeds Sustainability Institute, School of Built environment, Engineering and Computing, Leeds Beckett University
Leeds, United Kingdom

Hassim Tawfik
Computing Systems, School of Built environment, Engineering and Computing, Leeds Beckett University
Leeds, United Kingdom

Adam Hardy
Leeds Sustainability Institute, School of Built environment, Engineering and Computing, Leeds Beckett University
Leeds, United Kingdom

Roz Wyatt-Millington
Computing Systems, School of Built environment, Engineering and Computing, Leeds Beckett University
Leeds, United Kingdom

Abstract
This paper proposes a load scheduling approach for a residential home in an islanded PV micro grid scenario based on a Genetic Algorithm (GA). The primary aim is to inform on how a Demand Side Management (DSM) could reduce the capital cost of the residential home and operational cost of the microgrid by minimizing the use of fossil fuel generator. The research study proposes and describes the design for load allocation scheduling to achieve utilization of solar PV resources optimally. The proposed scheme is based on the time-of-use (TOU) and improvement of electricity users' comfort. The demonstration of the concept is presented and discussed based on a smart single home scenario using a solar PV microgrid and battery in a rural community of Enugu State, Nigeria.

Keywords—Microgeneration, Appliance Scheduling, DSM, Genetic Algorithm.

I. INTRODUCTION

Micro-grids can combine both fossil fuel and renewable energy resources to provide power to buildings [1], though managing these to be reliable, cost-effective and low-carbon is not straightforward. *Islanded* micro grids have no direct connection to national electricity infrastructure and so often need fossil fuel-powered generators to balance energy demand, since renewable energy sources are intermittent and variable [2][3]. A further complication for micro grid management is variations in energy demand of occupants of buildings [4]. To combat these complexities and variations, Demand-Side Management (DSM) is needed. DSM shifts energy usage from peak, to off-peak hours, [5, 6] thus, bringing demand within the limit of the available wattage provided by the microgrid [7]. DSM can improve energy efficiency and user comfort with cost minimization [8] and has previously been used in microgrids for residential dwellings [9].

Other challenges for micro-grids exist, associated with having multiple power supplies, user time-of-use preferences, and engaging energy users to actively manage their demand [10]. Demand Response (DR) programs are type of DSM that promote the electricity users' participation in shifting their energy consumption to reduce peak power demand [11]. DR can be price-based where the energy user is at liberty to minimize energy consumption due to increase in energy price [12], or load-based, often called *incentive based*, where the Electricity providers have direct control of a portion of a user's energy use for a certain period in exchange for incentive payments.

Energy consumption in homes is complex, involving multiple appliances, thus, machine learning has previously been applied to optimize how microgrids operate [13]. Previous work has focused on micro-grids in built up areas, yet remote areas are often more prone to inconsistent power supply and have more potential for micro generation. Thus, remote areas could also benefit from micro-grids and DSM.
This paper proposes a load scheduling approach for a residential home in an islanded PV micro grid scenario based on a Genetic Algorithm (GA). The primary aim is to inform on how a Demand Side Management (DSM) could reduce the capital cost of the residential home and operational cost of the microgrid by minimizing use of fossil fuel generator. The research study proposes and describes the design for load allocation scheduling to achieve utilization of solar PV resources optimally. The proposed scheme is based on the time-of-use (TOU) and improvement of electricity users' comfort. The demonstration of the concept is presented and discussed based on smart single home scenario using a solar PV microgrid and battery in a rural community of Enugu state, Nigeria. The paper is divided into two phases: (i) a systematic review of domestic energy use and (ii) the proposed energy management algorithm.

II. GENETIC ALOGRITHMS FOR THE MICROGRID

GA is a heuristic optimization search method that mimics the natural evolution to solve problems. This can be achieved by encoding parameters into a sequence using a binary representation, referred to as the *gene*, which can be combined into chromosomes. Sets of chromosomes, or *populations*, pass through a process of natural selection by mating and mutation to create new offspring. Selective pressure based on goodness of fit (fitness of solution evaluation) of a defined function leads to an optimal solution [14]. A flowchart for GA is presented in Figure 1.

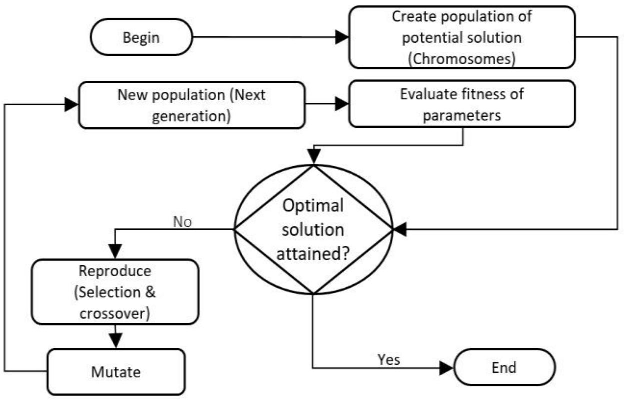

Fig 1, Typical GA process

Various evolutionary techniques have been previously used in load allocation and optimizing microgrid design; Table 1 summarizes the success of Genetic algorithm (GA), Bat Algorithm (BA), Hybrid Bat, Tugachi, Binary Particle Swamp Optimization (BPSO), Ant Colony Optimization (ACO) and, the variables used.

Table 1, Summary of GA techniques

Related Works	Methods	Parameters Used	Objective & Achievement
[15] A. Chakir et al. (2019)	GA	Input used: (T, G), P_{load} State of battery with its maximum state of charge Power: SOC_{max}, $P_{battmax}$ P_{grid}, E_i	For energy user electricity satisfaction. Authors claimed proposed algorithm minimised operational energy losses in homes.
[16] U. Latif et al (2018)	BA and Hybrid Bat GA	Total Number of appliances for Scheduling (APP), P, MaxIterP, POP, and location of ith bat	For cost optimisation. Authors claimed Hybrid Bath GA outperformed BA for cost reduction and Peak-to-Average Ratio.
[17] A. Ahmed et al, (2016)	GA	The ON/OFF state of appliance was used as chromosome pattern and Number of household appliance N was used as length of chromosomes	For Residential sector incorporation into DSM and RESs integration. Authors claimed that the algorithm reduced energy consumption expenses by 35%.
[18] X. Jiang & C. Xiao, (2019)	GA	Parameters are household condition, number of appliances, users electricity habit, time, priority opening time, working time, optional start and end time	To Minimise electricity cost based on user's response. Authors claimed to reduce electricity cost by29.0% and Peak-to-Average Ratio by 36.2%.
[19] S. Lin & C CHEN, (2016)	Tugachi – GA	Used real-time pricing, start slot, end slot, duration of each time slot, inelastic electricity, and contract capacity.	To reduce total purchase electricity. Authors claimed to achieve reduction in total purchase electricity with smaller number of epochs than the GA.
[20] S. Wang et al, (2019)	GA	PV capacity parameter and Home appliance parameter	Claimed reduction in electricity cost, improvement in load trend and increase of efficiency of energy storage system.
[21] Sahar Rahim et al, (2016)	GA, BPSO, and A CO.	Parameters of shiftable, elastic and fixed appliances. These include start time α_a(h), end time β_a(h), length of operation (LOT) τ_a(h), appliance power rating factor (energy) ρ_a(kWh). Also applied the combined model of time of use tariff and inclined block rates as the energy price.	To improve smart grid sustainability Cost effectively. Claimed to have achieved all objectives and that GA based energy management controller performed better than BPSO and ACO based energy management controller in terms of electricity bill reduction, peak to average ratio minimisation and comfort maximisation.
[22] S. L. Arun and M.P. Selvan, (2018)	GA	Noninterruptible and interruptible nonschedulable and, schedulable loads, battery, and renewable energy resources (RER)	To assist electricity users in bill reduction by proper time scheduling of loads and price evaluation.

from the reviewed works, it is clear that ga has been extensively applied in addressing load allocations and optimization problems. however, none has been able to address the comfort of rural residential users in an islanded pv microgrid scenario with dedicated energy storage system. therefore, the proposed ga will examine those challenges.

III. PROBLEM DESCRIPTION

This research project aims to optimize the design of a 4.4kW solar PV microgrid with batteries in the Aninri area of Enugu State, Nigeria, installed by the National Agency for Science and Engineering Infrastructure Abuja, Nigeria [23]. Data from this real world installation will be used to assess how a micro grid serving three homes as shown in Figure 2.

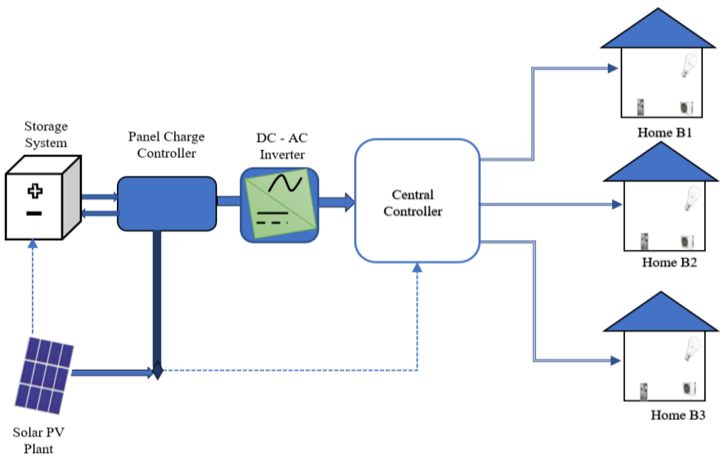

Fig 2, Case Study PV Microgrid

The proposed microgrid scheme consists of solar PV panel, the panel manager, a portable sized inverter system, an energy storage system (battery) and a central controller. In daylight hours, the solar PV panel generates DC that is passed to the storage system (battery). The charge controller decides whether to pass the generated DC to battery or to the inverter system depending on the intelligent signal received from the central controller. The inverter converts the generated DC to

AC. The AC is passed to the intelligent central controller to be used by the residential homes.

A. *Problem formulation*

The objective of the controller is to minimize total electricity cost and balance power consumption so that the available wattage is not exceeded at any particular time. To achieve this, for simplicity, appliances are assumed to be controlled using a time-of-use (TOU) tariff scheme so that additional energy generation can be stored during off peak hours and additional capacity offered at peak time. For simplicity in this study, the load profile of each home appliance follows pre-set conditions obtained from the study site. Figure3 shows the individual load contributions of the residential home. Using the equation that relates price, energy and required quantity of energy, the estimated capacity needed at any given time is given as:

Required amount (quantity in £) $= electricity\ tariff\ (C_P) \times energy\ (E)$
Where:

$$\text{energy E (KWh)} = power\ P\ \times time\ T\ (duty\ cycle)$$

And therefore:

$$P\ (kW) = \frac{E\ (kWh)}{T(h)}$$

Each appliance has an execution time of 24hr divided into duty cycle time (∂t) of 20 minutes each. Appliances can be shiftable (Ns) or nonshiftable ($\aleph n$) [24]. The GA's adjustable variable is the total allotted wattage $\wp_{ij}^{t}\ (in\ kW)$ where i the appliance, j is the load profile for each appliance i and t is the allotted time. Therefore, the total wattage is:

$$\wp_{ij}^{t} = P_{i1}^{t} + P_{i2}^{t} + P_{i3}^{t} \dots P_{in}^{t}$$

The total number of shiftable appliances can represented by $\aleph s$. Hence:

$$\aleph_i \in \aleph s$$

Therefore, two or more shiftable appliances of the same category in the residential home can be identified by a decimal notation:

For $\forall t = 1,2,3, \dots \mathbb{T}$ and $\forall i = 1,2,3, \dots \aleph_s$.

Where t represents the time index.

B. *Objective function*

The main objective of the GA is to reduce peak demand by optimum allocation and maximize power utilization from the solar PV microgrid. If we represent the rated power $\wp_{ij}^{t}\ (in\ kW)$ as the adjustable (decision) variable, j as the load phase for each appliance i and t as the allotted time; and then $g_{i,t}^{k}$ is taken as the supporting decision variable which is seen as the binary number (1,0) of the appliance i at given time t. Then, the cost function Υ_c is given as

$$\Upsilon_c = max \sum_{t=1}^{\mathbb{T}} \sum_{i=1}^{\aleph s} \sum_{j=1}^{\aleph_i} \left[\wp_{ij}^{t} * g_{i,t}^{k} \right] \quad (1)$$

The supporting binary decision variable is applicable as:
$g_{i,t}^{k} = 1$, when appliance i is turned ON at time t and
$g_{i,t}^{k} = 0$, when appliance i is turned OFF at time t

If we represent another supporting decision variable as the electricity user's baseline for ON/OFF status of the appliance i at time t as $h_{i,t}^{k}$, then the second objective tends to get additional wattage from the dedicated energy storage of the micro grid. The equation above mathematically forms the new objective function expressed as[25]:

$$\Upsilon_c = min \sum_{t=1}^{\mathbb{T}} \sum_{i=1}^{\aleph s} \sum_{j=1}^{\aleph_i} \left[\wp_{ij}^{t} \left[\mathbb{C}_t * g_{i,t}^{k} - \alpha_t * \epsilon\left(h_{i,t}^{k} - g_{i,t}^{k}\right)\right] * \partial t \right] \quad (2)$$

Where $\mathbb{C}_t$ the electricity price or the TUO is tariff at given time t; α_t is added incentive or additional wattage at a given time t; the decision time is represented as ∂t.

$h_{i,t}^{k} + g_{i,t}^{k} = 1$, therefore it means that $h_{i,t}^{k}$ and $g_{i,t}^{k}$ complement each other.

Provided that $\wp_{ij}^{t} \geq 0, \alpha_t > 0,\ \aleph s = 6, \mathbb{T} = 166$,
$\epsilon\left(h_{i,t}^{k} - g_{i,t}^{k}\right) = 1$, Only if$\left(h_{i,t}^{k} - g_{i,t}^{k}\right)$ is greater than zero,
But become $\epsilon\left(h_{i,t}^{k} - g_{i,t}^{k}\right) = 0$, only if $\left(h_{i,t}^{k} - g_{i,t}^{k}\right)$ is less than or equal to zero.

Where $\epsilon\left(h_{i,t}^{k} - g_{i,t}^{k}\right)$ binary (1,0) is indicator function that shows the status of the model. Hence, $\epsilon\left(h_{i,t}^{k} - g_{i,t}^{k}\right)$ indicates one (1) when extra wattage is not required but zero (0) when extra wattage is required and when there is need to minimize consumption by turning off some appliances during peak time. In other words, 1 means get additional support while 0 means no additional support. The study is subject to the following constraints from equation (1):

$$\sum_{t=1}^{\mathbb{T}} \sum_{i=1}^{\aleph s} \sum_{j=1}^{\aleph_i} \left[\wp_{ij}^{t} \left[\mathbb{C}_t * g_{i,t}^{k2} - \alpha_t * \epsilon\left(h_{i,t}^{k} - g_{i,t}^{k}\right)\right] * \partial t \right] \leq 10 \quad (3)$$

Therefore, the constraint tends to regulate the amount of electricity tariff the user can afford on daily bases, which should be less than or equal to £10.

We considered only the shiftable appliances as the flexible load at time range specified by the users. Hence, $\nu_i$and ψ_i are the start and end of the appliance scheduled time range;
It is important to ensure that wattage is available at the needed time interval. Hence,

$$\sum_{\nu_i}^{\psi_i} g_{i,t}^{k} \geq \mathrm{I}_i \quad (4)$$

I_i is suitable time duration for the appliance i to complete operating cycle. Therefore, the constraint in equation below is required for continuous operation appliances[26]:

$$\sum_{\nu_i}^{\psi_i - (\mathrm{I}_i - 1)} g_{i,t}^{k} * g_{i,t+1}^{k} * g_{i,t+2}^{k} \cdots g_{i,t+(\mathrm{I}_i-1)}^{k} \geq 1 \quad (5)$$

The constraint in the equation below allows the each appliance to start operation after the other:

$$\nu_{i2} \geq d_{i1} + \mathrm{I}_i \quad (6)$$

The second constraint means that at each daily operating cycle, the total available capacity or supplied power (W) must be greater than or equal to the total sum of individual load (total estimated wattage in W):

$$\wp_{ijsup}^{t} \geq P_{i1}^{t} + P_{i2}^{t} + P_{i3}^{t} \quad (7)$$

Moreover, every residential home energy user has preference of appliance use based on LOT time constraints.

a) The Discomfort parameter

The comfort parameter l ensures the reduction in mismatch that occur between the baseline and optimal scheduling parameters. The adjustment and shifting of use are taken as discomfort in this study. Therefore, the objective function in equation above can be reduced by the user as:

$$l := \sum_{t=1}^{\mathbb{T}} \sum_{i=1}^{\aleph_S} \sum_{j=1}^{\aleph_i} \left(h_{i,t}^{k} - g_{i,t}^{k}\right)^2 \quad (8)$$

We can then add the discomfort level in the objective equation 1. Hence the adjusted objective the user tends to minimize:

$$\Upsilon_c + \propto l = min\Upsilon$$

C. *Residential Home Appliances*

This study, for simplicity uses one of the homes in the case study on which to base the GA. The home proposed is a semi-detached bungalow with multiple appliances each with definite length of operation time (LOT) or duty cycle time which is used to generate an energy consumption vector [27, 28]. Figure3 shows the total estimated load and the available load. This study is based on the actual solar PV plant from the National Agency for Science and Engineering Infrastructure Abuja, Nigeria [23].

Tables 2 and 3 show the proposed energy consumption in the case study house for non-shiftable appliances [29], which have fixed energy consumption at each time slot, and shiftable appliances, which have adjustable energy consumption at each time slot and can be sub-categorized as interruptible and non-interruptible. C. Chen et al (2013) and Agnetis et al (2013) described these as:

- *Non-interruptible shiftable appliances* (N_a) : appliances consume the same amount of energy for every hour without being interrupted. The appliances in this category cannot be turned OFF or ON during their time of operation. Moreover, the electricity consumption of these appliances is not adjustable. e.g. washing machines.
- *Interruptible shiftable appliances*: The appliances in this category can be turned OFF or ON during their operating time. Some appliances in this category also depend on the environmental (weather) condition during their operating time. e.g. iron, cooker, refrigerator and air conditioner.

Table 2, Non-shiftable appliances in case study building

Load ID	Appliance	Power Rating (kW)	Category description
N_{a1}	Energy Bulb (for indoor and security lights)	0.20	Non-shiftable load that can operate for 24 hours daily. Their minimum and maximum power loads are between 0kW to 0.20kW during their operating cycle. Can consume the energy of around 0.16kWh daily.
N_{a2}	Computer system (desktop, laptop, printer) and phones	0.30	Non-shiftable load that can operate for 24 hours daily.
N_{a3}	Television and accessories(TV, Radio,	0.25	Non-shiftable load that can operate for 24 hours daily.

Table 3, Shiftable parameters in case stusy building

Load ID	Appliance (× Available Number)	Start – End Time	Power Rating (kW)		Daily LOT (h)	Daily Require d Energy (kWh)	Category Description
S_{a1}	Refrigerator (*2)	1am – 12am	0. 4	0.8	23	18.4	Environment ally weather controlled.
S_{a2}	Washing Machine (*1)	9am – 10.45 am	0. 6	0.6	2.45	1.47	Non-interruptble Shiftable load
S_{a3}	Electric cooker Hob (*1)	6am – 8.30a m	0. 5	0.5	2.30	1.15	Interruptible Shiftable load
S_{a4}	Air Conditioner (*2)	8pm – 11pm	0. 55	1.1	4	4.4	Environment ally weather controlled Shiftable load.
S_{a5}	Oven (*1)	3pm – 4.50p m	2. 3	2.3	1.50	3.45	Interruptible Shiftable load
S_{a6}	Electric Iron (*1)	6am – 7am	1	1	0.30	0.3	Interruptible shiftable load

S_{a1} is environmentally weather controlled shiftable load that can operate 24 hours daily. It can operate between 0kW to 0.38kW during their operating cycle and also consume the estimated energy of 3.43kWh daily. The minimum and maximum power loads are between 0kW to 0.38kW during their operating cycle. Can consume the estimated energy of 3.43kWh daily.

S_{a2} is Non-interruptble Shiftable load with three cycles of operation (washing, rinsing and drying). Power load can vary between 0.52kW to 0.65kW. The full cycle of operation takes about 45mins – 150 mins. The power load of cloth dryer is about 0.19kW – 2.97kW.

S_{a3} is interruptible Shiftable load that can be used more than once daily. The operating power load varies between 0.75kW to 2.35kW.

S_{a4} is Environmentally weather controlled Shiftable load with peak of 2.75kW working hours and 0.25kW during the compressor off period. Normal AC (2.5-ton) can consume 31.15kWh of energy daily. Can consume energy of 1.72kWh daily.

S_{a5} is Interruptible Shiftable load that can operate more than once daily. The minimum and maximum loads are between 1.25kW to 0.93kW during the operating cycle.

S_{a6} is Interruptible shiftable load operating more than once daily. Their minimum and maximum power loads are between 0kW to 2.4kW during the operating cycle. Can consume the energy of 2kWh daily.

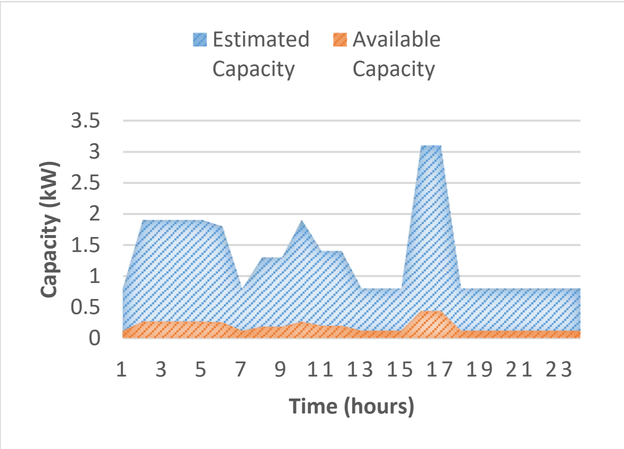

Fig3: the total hourly scheduled load and the available capacity

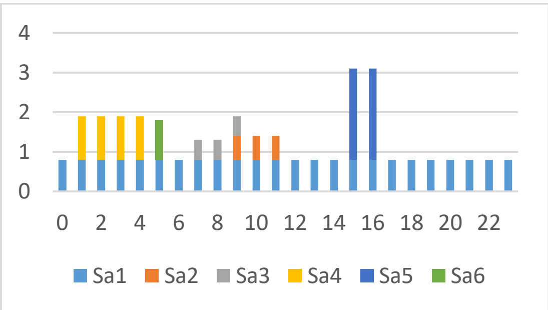

Fig4: Daily individual load contributions

D. *Appliance Operation Time*

User preference determines the appliance operation period. The minimum start and end time for each scheduled load on this case study is specified in fig5 with colour coding for shiftable appliance scheduling and allocated load points. See the appendix for the detailed analysis.

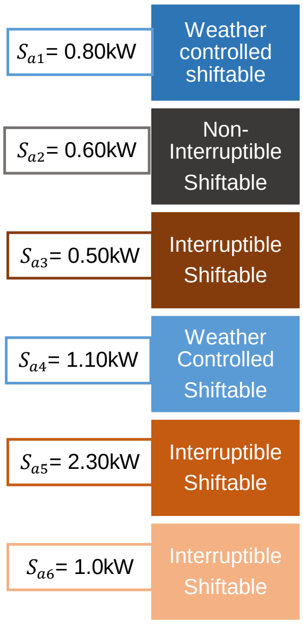

Fig5: Colour coding for shiftable appliance Scheduling

GA Solution Representation

The appliance is shceduled based on priority during the 24h period. Hence, a certain appliance can be preferred for operation at a particular time depending on the time of use and category of the load (i.e controllable, weather controlled etc.). From fig6, the scheduled appliance profile in fig5 is further described and classified based on the actual daily demand of the home.

Node Slot	Shiftable Load / Range	S_{a1}	S_{a2}	S_{a3}	S_{a4}	S_{a5}	S_{a6}	Active Demand (kW)
6	0 – 3	1	0	0	1	0	0	4.6
3	4 – 7	1	0	1	1	0	1	5.8
4	8 – 10	1	1	1	0	0	0	4.6
2	11 – 15	1	1	0	0	1	0	6.9
5	16 - 19	1	0	0	0	1	0	5.5
1	20 - 23	1	0	0	0	0	0	2.4
Total								30

Fig6: Proposed GA based solution representation

It is envisioned that the evolutionary operation of proposed GA for load allocation would produce a solution set which represent optimal search of parameters under the active demand scenarios. A set of the generated binary values would determine state (ON/OFF) of loads in the Node Slot (see fig6). The GA would evolve the set of solution using the proposed format guided by the objective function described in section B.

IV. Summary and Conclusion

The current state-of-art in micro generation technology and energy management reviewed showed that many different mathematical models and optimization techniques have been explored for residential home scheduling using DSM and more specifically DR. In remote regions, microgeneration and renewable energy resources serve as the major source of electricity but these can be expensive especially where battery storage is needed. It is possible to use GA to optimize micro-grids and reduce the initial capital cost of the batteries and peak loads. A design for such a micro-grid is proposed, this would use the objective function to optimize the performance.

ACKNOWLEDGMENT

My special gratitude goes to Petroleum Technology Development Fund (PTDF), Nigeria for their financial and moral supports during this work.

References

1. IRENA, *INNOVATION LANDSCAPE FOR A RENEWABLE-POWERED FUTURE: SOLUTIONS TO INTEGRATE VARIABLE RENEWABLES.* International Renewable Energy Agency, Abu Dhabi., 2019.
2. James A. Momoh, *Smart Grid: Fundamentals of Design and Analysis.* Wiley-IEEE Press, 2012.
3. Samuel C.Johnson et al, D.J.P.S.M.A.D.D.R.E.W., *Evaluating rotational inertia as a component of grid reliability with high penetrations of variable renewable energy.* Energy, 2019. **Volume 180,** : p. Pages 258-271.
4. P Du and N Lu, *Appliance Commitment for Household Load Scheduling.* IEEE TRANSACTIONS ON SMART GRID, 2011. **VOL. 2**(2).
5. CherrelleEid et al, E.K., Mercedes Valles, Javier Reneses, Rudi Hakvoort, *Time-based pricing and electricity demand response: Existing barriers and next steps.* Utilities Policy, 2016. **40**: p. Pages 15-25.
6. Sarah J. Darby & Eoghan McKenna, *Social implications of residential demand response in cool temperate climates.* Energy Policy, 2012. **49**: p. Pages 759-769.
7. Pei-yangGuo et al, D.-y., JacquelineLam, Victor O.K. Li, *The Future of Wind Energy Development in China.* Wind Energy Engineering, 2017: p. 75-94.
8. D.Li et al, W.-Y.C., H.Sun,, *Demand Side Management in Microgrid Control Systems.* Advanced Control Methods and Renewable Energy System Integration

2017: p. Pages 203-230.

9. C. W. Gellings, *The concept of demand-side management for electric utilities.* in Proceedings of the IEEE, . **73**(10): p. pp. 1468-1470, Oct. 1985.
10. C. Abreu et al, D.R., P. Machado, J. A. Peças Lopes and M. Heleno, *Advanced Energy Management for Demand Response and Microgeneration Integration.* 2018 Power Systems Computation Conference, 2018: p. 1-7.
11. Goran Strbac, *Demand side management: Benefits and challenges.* energy Policy, 2008. **36**(12): p. 4419-4426.
12. S. Nithin, *ICT Application of DSM.* Smart Micro Grid, 2020.
13. Ming-Wen Tsai et al , T.-P.H., and Woo-Tsong Lin,, *A Two-Dimensional Genetic Algorithm and Its Application to Aircraft Scheduling Problem.* mathematical Problems in Engineering, 2015. Volume 2015 p. 12.
14. D. E. Goldberg and K. Deb, *a comparative analysis of selection schemes used in genetic algorithms*. 1991: Morgan Kaufmann Publishers, Inc.
15. A. Chakir et al., M.T., F. Moutaouakkil et al., Mohamed TabaaFouad MoutaouakkilHicham MedromiMaya Julien-SalameAbbas DandacheKarim Alami, *Optimal energy management for a grid connected PV-battery system.* Energy Report, 2019.
16. U. Latif et al, N.J., S. S. Zarin, M. Naz, A. Jamal and A. Mateen, Krakow, , *Cost Optimization in Home Energy Management System Using Genetic Algorithm, Bat Algorithm and Hybrid Bat Genetic Algorithm.* 2018 IEEE 32nd International Conference on Advanced Information Networking and Applications (AINA),, 2018: p. pp. 667-677.
17. A. Ahmad et al, N.J., S. Ahmad, S. Saud, U. Qasim and Z. A. Khan, , *Realistic Home Energy Management System Using Exogenous Grid Signals.* 2016 19th International Conference on Network-Based Information Systems (NBiS), Ostrava, , 2016: p. pp. 458-463.
18. X. Jiang and C. Xiao, *Household Energy Demand Management Strategy Based on Operating Power by Genetic Algorithm.* in IEEE Access, 2019. **7**: p. 96414-96423.
19. S. Lin and C. Chen, *Optimal energy consumption scheduling in home energy management system.* International Conference on Machine Learning and Cybernetics (ICMLC), Jeju, 2016, 2016: p. 638-643.
20. S. Wang et al., *Genetic Algorithm Based Optimal Strategy for Smart Home Energy Management System with Solar Power and Electric Vehicle.* 4th International Conference on Mechanical, Control and Computer Engineering (ICMCCE), Hohhot, China, 2019, , 2019: p. pp. 979-9793.
21. Sahar Rahim et al, *Exploiting heuristic algorithms to efficiently utilize energy management controllers with renewable energy sources.* energy and building, 2016.
22. S. L. Arun and M. P. Selvan, *Intelligent Residential Energy Management System for Dynamic Demand Response in Smart Buildings.* in IEEE Systems Journal, , June 2018, 2018. **vol. 12**(2): p. pp. 1329-1340.
23. D.O.Akinyele et al, R.K.R., N.K.C.Nair, *Global progress in photovoltaic technologies and the scenario of development of solar panel plant and module performance estimation − Application in Nigeria*

Renewable and Sustainable Energy Reviews, 2015. **48**: p. Pages 112-139.

24. C. Chen et al, J.W., Y. Heo and S. Kishore, , *MPC-basedappliancescheduling for residential building energy management controller.* in IEEE Transactions on Smart Grid,, 2013. **4**(3): p. pp. 1401-1410.
25. C. Wang et al, Y.Z., J. Wang, P. Peng, *A novel traversal-and-pruning algorithm for household load scheduling.* Applied Energy, 2013. **102** p. pp. 1430-1438.
26. U.E. Ekpenyong et al, J.Z., X. Xia, *An improved robust model for generator maintenance scheduling.* Electr. Power Syst. Res., , 2012. **92** p. pp. 29-36.
27. Agnetis et al, G.d.P., Paolo Detti, and Antonio Vicino, *Load Scheduling for Household Energy Consumption Optimization.* IEEE TRANSACTIONS ON SMART GRID, 2013. **4**(4).
28. F. A. QAYYUM et al, M.N., A. S. KHWAJA, A. ANPALAGAN, L. GUAN1 AND B. VENKATESH1, *Appliance Scheduling Optimization in Smart Home Networks.* IEEE Access, Appliance Scheduling Optimization in Smart Home Networks, 2015.
29. !!! INVALID CITATION !!! [37-40].

Appendix

The load allocation table

Hourly Schedule	S_{a1}	S_{a2}	S_{a3}	S_{a4}	S_{a5}	S_{a6}	Estimated Hourly $\wp_{ij}^{t}$(kW)	Available $\wp_{ijsup}^{t}$(kW)	Demand Probability		
									35%	65%	95%
0							0.80	0.11	0.38	0.71	1.05
1							1.90	0.26	0.28	0.52	0.76
2							1.90	0.26	0.28	0.52	0.76
3							1.90	0.26	0.66	1.24	1.81
4							1.90	0.26	0.28	0.52	0.76
5							1.80	0.25	0.28	0.52	0.76
6							0.80	0.11	0.63	1.17	1.71
7							1.30	0.18	0.80	1.50	2.18
8							1.30	0.18	0.45	0.84	1.24
9							1.90	0.26	0.49	0.91	1.33
10							1.40	0.19	0.49	0.91	1.33
11							1.40	0.19	0.49	0.91	1.33
12							0.80	0.11	0.28	0.52	0.76
13							0.80	0.11	0.28	0.52	0.76
14							0.80	0.11	0.28	0.52	0.76
15							3.10	0.43	1.10	2.00	2.95
16							3.10	0.43	1.10	2.00	2.95
17							0.80	0.11	0.28	0.52	0.76
18							0.80	0.11	0.28	0.52	0.76
19							0.80	0.11	0.28	0.52	0.76
20							0.80	0.11	0.28	0.52	0.76
21							0.80	0.11	0.45	0.85	1.24
22							0.80	0.11	0.66	1.23	1.81
23							0.80	0.11	0.66	1.23	1.81
Total (kWh)	18.4	1.8	1.5	4.4	4.6	1	32.7	4.4	11.4	21.3	31.1