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An intelligent load manager for PV powered off-grid residential houses

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ABSTRACT

This paper proposes a management system based on certain rule set implemented by Modified Mild Intrusive Genetic Algorithm (MMIGA) that will optimize the load allocation to match the house owner affordable solar system inverter. The algorithm optimized load allocation in real time in both sufficient and insufficient supplies of energy. A daily load discrimination profile is first established followed by the development of priority matrix for the respective time of the day; MMIGA is then used to intelligently evolve a sequence of bits, which are then implemented by the hardware while observing certain set of rules. The result shows that about 98.88% allocation was obtained in the sufficient case scenario while 99.84% allocation was achieved in the insufficient scenario. The proposed algorithm meets the objective of being cost effective, smart, simple to use and can be severally applied to different load profiles.

Introduction

The building sector represents one of the largest potentials for energy efficiency and reduction of greenhouse gas emissions. The intelligent use of load and its optimal management is one of the major concerns of utility managers, providers and consumers of energy. Load management in the general sense is the process of balancing the supply of electricity on the network with the electrical load by adjusting or controlling the load rather than the power station output. It is also considered as a set of objectives designed to control and modify the patterns of demand of consumers. It allows limiting or shifting peak load from on-peak to off-peak periods. This can be achieved by direct intervention of the utility in real time, by the use of frequency sensitive relays triggering circuit breakers, or by time clocks, or by using special tariffs to influence consumer behavior.

However, in solar photovoltaic power system, the concept of load management is viewed from the perspective of controlling the load to ensure that the insolation over a period is able to carry the load. Also, the storage system is put into focus. The storage cannot make infinite amount of energy available to the load, thus acquired and available energy must be utilized in the most efficient way possible. This gives credence to research efforts towards developing automatic systems suitable for direct load control, with the goal of making loads active and intelligent.

In a solar photovoltaic power system, a major goal of load management is to ensure that the more critical loads are operated at the expense of the less critical loads and that the storage (battery) is protected from excessive discharge (Groumpos and Papergeorgiou, 1991). Therefore by definition, load management in solar photovoltaic power system is a strategy that involves manipulating the controllable loads to favorably modify system load curve in correspondence to the economically available generation (Groumpos and Papergeorgiou, 1991). This implies that, load management is a mindful maneuvering of the consumer load profile to improve system's efficiency. Research efforts have focused on development of automation systems to improve household load management.

Various techniques have been used for studying and development of different load management strategies such as the use of data mining approach in the development of an energy management system for a naphtha reforming plant (Velazquez et al., 2012), the use of SCADA based software where set points of various subsystems are optimized in real time by means of an integrated systems approach (Du-Plessis et al., 2013; Cristian-Dragos and Adrien, 2012), supervisory strategy with the help of fuzzy logic and graphical methods (Zhang et al., 2012), multi-objective genetic algorithm approach in which the time allocation of domestic loads is optimized within a planning period, the use of an optimization energy system model such as the Integrated MARKAL EFOM System (Fehrenbach et al., 2014) and multi-period gravitational search algorithm techniques (Marzband et al., 2014).

It has been demonstrated that effective load management has positive correlation with energy efficiency and electricity bill. A multi-objective genetic algorithm was used to solve a multi-objective model to optimize the time allocation of domestic loads within a planning period of 36 h, in a smart grid context by Soares et al. (Soares et al., 2014).

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In their work, the management of controllable domestic load was used to minimize the electricity bill. Economic potential for thermal load management with virtual power plants consisting of micro-cogeneration plants, heat pumps and thermal storage within the residential sector was a concern in Fehrenbach et al. (2014). An expert Energy Management System (EEMS) for optimal operation of wind turbines and other Distributed Energy Resources (DERs) in an interconnected micro-grid was a focus in Motevasel and Seifi (Motevasel and Seifi, 2014) with the objective of finding the optimal set points of DERs and storage devices, in such a way that the total operation cost and the net emission are simultaneously minimized. Faxas-Guzmán et al. (Faxas-Guzmán et al., 2014) has developed priority load control algorithm in order to provide a better energy management efficiency that can guarantee energy supply for the critical loads in a standalone PV system. The implementation of this algorithm showed that it is capable of increasing the reliability of the system and the end-user satisfaction. Energy management for a standalone hybrid system that involves wind/PV/battery/fuel cell was proposed by Feroldi et al. (Feroldi et al., 2013). In their work, an optimal sizing methodology based on genetic algorithms was designed for standalone system. Similarly, Wang et al. (Wanga et al., 2011) proposed a topology and energy management strategy of a standalone hybrid PV system, which can solve the overcurrent problem of the storage battery, and verifies the effectiveness and feasibility of the energy management strategy. The results of their work showed that constant-voltage and current-limited control of the battery are realizable. It was also revealed that battery does not only work in optimal charging and discharging state, but also satisfies the energy storage requirements of the system. In the same manner, Urtasun et al. (Urtasun et al., 2014) developed an energy management strategy for a standalone system in which the battery and the diesel generator are centralized while the loads and the PV generators are distributed and are all connected to the grid. The developed energy management scheme simplifies the complex system in a cheaper and more reliable manner. The strategy also optimizes the efficiency and operating life of the diesel generator. However, Chauhan and Saini (Chauhan and Saini, 2014) are of the opinion that more research and efforts are required to further improve batteries' durability and performance with a focus on lowering their cost.

The use of energy management in building applications has also been reported in the literature. Zhang et al. (Zhang et al., 2012) present an energy management strategy for a commercial building (supermarket application) with the objective of reducing the electricity bill and the CO_2 emissions of the building, using photovoltaic (PV) and storage systems. Their simulation results using economic and ecological indicators revealed that the energy bill cost and the CO_2 emissions were reduced with the proposed energy management scheme. Figueiredo & Martins (Figueiredo and Martins, 2010) were concerned with Energy Production System Management (EPSM) of a building which allows the incorporation of a complete set of renewable energy production and storage systems (Figueiredo and Martins, 2010). They also presented a Building Automation System (BAS) where the Demand Side Management (DSM) is fully integrated with Energy Production System. Similarly, Multi-objective Genetic Algorithm (MOGA) was developed by Pervez et al. (Pervez et al., 2013) to achieve energy efficiency and management in a building. This allows energy saving while achieving a high comfortable environment. A novel strategy for Building Energy Management System (BEMS), which efficiently controls energy flows in a building so as to minimize the total cost of energy for a finite period was proposed by Kang et al. (Kang et al., 2014) The Demand Response (DR) event during the period was also considered.

However, none of the aforementioned studies take into consideration the initial economy of household owners. In developing countries, it is almost a common issue that most households with medium income earners, having interest in the use of renewable energy system as an alternative to epileptic power supply, hardly can afford the required size of solar power inverter system required to power their residences. This inability requires the development of simplified and cheap technologies that are able to match the power provision with the economy of house owners. This current work therefore proposes the use of Modified Mild Intrusive Genetic Algorithm (MMIGA) for intelligent load management of PV powered off-grid residential houses. This intelligent load management system is capable of maintaining the maximum limit of energy consumption within the economic capability of the house owner.

Proposed load management scheme

The frame of operation of the proposed system is illustrated in Fig. 1. It consists of an appropriately/affordably sized inverter system, maintenance free deep cycle battery storage system connected to a bank of solar panel through a solar charge controller. The inverter systems generate the AC and pass on the output to the load through the intelligent load manager (presented in this paper), which produces the load profiles based on certain criteria as obtained and made available by

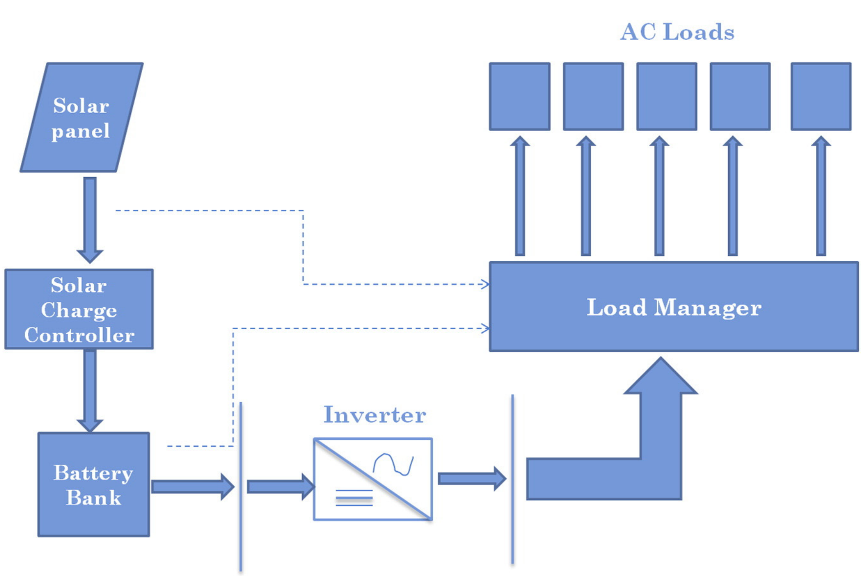


Fig. 1. Architecture of the scheme.

Table 1
Energy audit of a typical medium income 4 bedroom residential house.

Electrical appliances		Number in use	Wattage (W)	Total wattage (W)	Daily duty cycle (h)	Daily energy consumed (Wh)
Lightings	Indoor Lights 1	8	15	120	5	600
	Indoor Lights 2	6	15	90	4	360
	Security Lights	5	25	125	6	750
Television set		1	150	150	9	1350
DVD player		1	35	35	9	315
Satellite decoder		1	30	30	9	270
Antenna module		1	25	25	9	225
Computer systems bay	Desktop PC	1	150	150	3	450
	Mobile phones	5	15	75	3	225
	Laptop PC	2	65	130	2	260
Ceiling fan 1		1	100	100	6	600
Ceiling fan 2		3	100	300	3	900
Table fan		1	35	35	4	140
Refrigerator unit		1	400	400	9	3600
Washing machine		1	500	500	1	500
Water pump		1	750	750	0.5	375
Kitchen appliances	Blender	1	300	300	0.25	75
	Microwave oven	1	850	850	0.5	425
Water heater		1	800	800	1	800
Passageway lights		3	15	45	9	405
Ghost load		1	100	100	3	300
Sum total		4475	5110		12,925	

some installed sensors. The performance and the development of the load manager proposed in this paper are based on the actual energy audit of a typical 4-bedroom residential house (medium income house owner) in Wakajaiye village, Ibadan, (latitude 7.3964° N, longitude 3.9167° E).

Energy audit

The total electrical load was evaluated by formulating an approximated but comprehensive list of all appliances that are used in the apartment. The listing is as shown in Table 1.

Based on the specified load in Table 1, the total estimated load (watt), P_D shown in Table 1 is given by Eq. (1),

$$P_D = \sum_{i=1}^{n} N_i W_i \tag{1}$$

where W_i is the wattage rating of the ith residential appliance and N_i is the number in use of the ith residential appliance. Thus, the total estimated load P_D is 5110 W, which directly indicates that the sizing of the solar powered inverter system should be done to handle the estimated peak load of 5.1 kW. However to account for difference in time for the utilization of the appliances, a demand factor of 0.75 was applied to give a total required power of 3.8 kW. Using a power factor of 0.8, then an inverter of 4.8 kVA is required. The available inverter rating in the market corresponding to the load requirement is 5.0 kVA. However, in a developing economy like that of Nigeria, it is generally observed that the economic status of these house owners limit them in the size of solar based inverter system that can be purchased. A random interview of owners of similar sized residential houses in the selected area showed that such a group will not be able to acquire the needed 5.0 kVA solar powered inverter system. A common view among these household owners indicates that they might be able to save up or access a community loan to purchase a 2.5 kVA inverter system (which is a far cry from the energy size of the household). It is also worth noting that despite the situation of energy shortage in most developing countries, there is no specific policy that supports the funding of off-grid residential houses by financial institution, as such, house owners are left to provide for energy within their economic limit. In view of the economic capability of this group of people and the need to improve access to electricity, a management system that will optimize the load allocation to match the economically sized 2.5 kVA solar powered inverter system is developed based on the load classification and prioritization.

Load classification and prioritization

Priority classification groups the total household appliances into eight (8) categories denoted by L1 through to L8 as shown in Table 2. Appliances, which work almost together, were grouped to belong to the same category. L1 is the highest priority load, which comprises appliances that meet the basic need of the household. L2 comprises computer equipment, which are all operated at the computer bay. L3

Table 2
Load classification.

Priority classification	Electrical appliances		Total wattage	System classification
L1	Lights	Indoor lights 1	120	Uncontrollable
		Passage way light	45	
	Television set		150	
	DVD player		35	
	Satellite decoder		30	
	Antenna module		25	
	Ceiling fan 1		100	
	L1 Total		505	
L2	Computer systems	Desktop PC	150	Uncontrollable
		Ghost load	100	
		Mobile phones	75	
		Laptop PC	130	
	L2 Total		455	
L3	Refrigerator		400	Controllable
	Ghost load		0	
	L3 Total		400	
L4	Indoor light 2		90	Controllable
	Passageway lights 2		45	
	Security light		125	
	Ceiling fan 2		200	
	Total		460	
L5	Washing machine		650	Controllable
L6	Water pump		750	Controllable
L7	Kitchen appliance	Blender	300	Controllable
		Microwave oven	850	
	Total		1150	
L8	Water heater		800	Controllable

Table 3
Scheduled hourly loads.

Hours of the day	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	0
L1	505	505	505	505	505	505	505	505	505	505	505	505	505	505	505	505	505	505	505	505	505	505	505	505
L2	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455	455
L3										400	400	400	400	400	400									
L4	460	460	460	460	460	460															460	460	460	460
L5																650	650	650						
L6									750															
L7							1150	1150											1300	1300				
L8					800	800																		
Total load	1420	1420	1420	1420	2220	2220	2110	2110	1710	1360	1360	1360	1360	1360	1360	1610	1610	1610	2260	2260	1420	1420	1420	1420
x demand factor (0.75)	1065	1065	1065	1065	1665	1665	1583	1583	1283	1020	1020	1020	1020	1020	1020	1208	1208	1208	1695	1695	1065	1065	1065	1065
Total controllable load	460	460	460	460	1260	1260	1150	1150	750	400	400	400	400	400	400	650	650	650	1300	1300	460	460	460	460

through L8 carry equal priority but will be assigned the highest priority load during their hours of operation. Summarily, the priorities attached to each load are not fixed but rather varies from one period to the other depending on the appliances that are most crucial to user at a particular period of the day during the 24 h cycle, and also on whether the load category is according to the system classification controllable or uncontrollable, as the uncontrollable loads carry the highest priority during their hours of operation.

Scheduling and profiling of hourly load

The load scheduling is based on the projected appliances that become necessary to be used at a particular period during the 24 h cycle. The uncontrollable loads (L1 and L2) demand instantaneous power and are therefore scheduled to run all through the cycle. The remaining load categories are controllable i.e. their periods of operation are deferrable and do not demand instantaneous power. The uncontrollable loads are spread over the 24 h cycle of operation by allowing each of them to be operated only at the time it will be mostly needed in such a way that the peak load at any point in time is reduced, as shown in Table 3.

From Table 3, the projection is based on the maximum expected generation obtainable from either the array or the battery at any time. Load categories L1 and L2 are scheduled to receive instantaneous power through the 24 h cycle. The remaining load categories L3 and L8 are distributed. The contribution of the controllable load to the total hourly load is shown to be at maximum between the hour of 04:00 and 06:00. Based on the priority load classification, scheduling and profiling of hourly load, the load profile of the typical house is depicted in Fig. 2.

Load switching plan and algorithm

The load switching scheme for the operation of load manager is a set of predefined rules. The rules are based on the hourly load scheduled shown in Table 3. The highest priority load to be served at a particular hour will be the uncontrollable load for that hour. If the available energy from the solar system installation is insufficient to meet all the loads scheduled for that hour, the least priority load (which may be one of the controllable loads) is disconnected. This was implemented using MMIGA developed in this work. The proposed algorithm seeks to optimize load allocation in real time under the condition of both sufficient

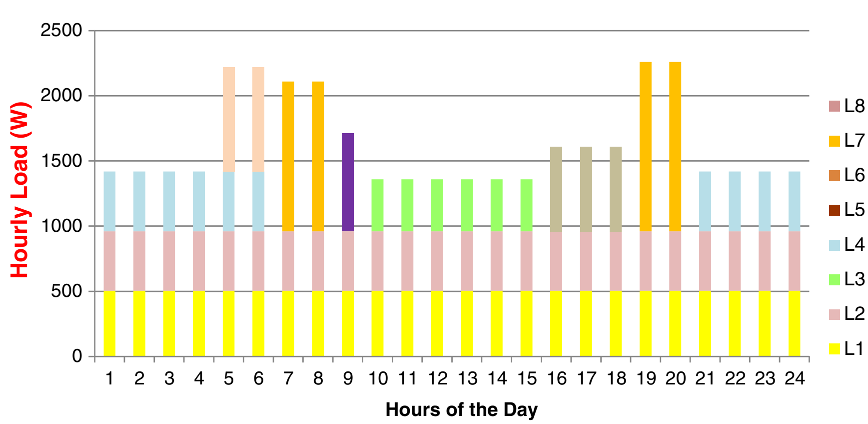


Fig. 2. The daily load profile.

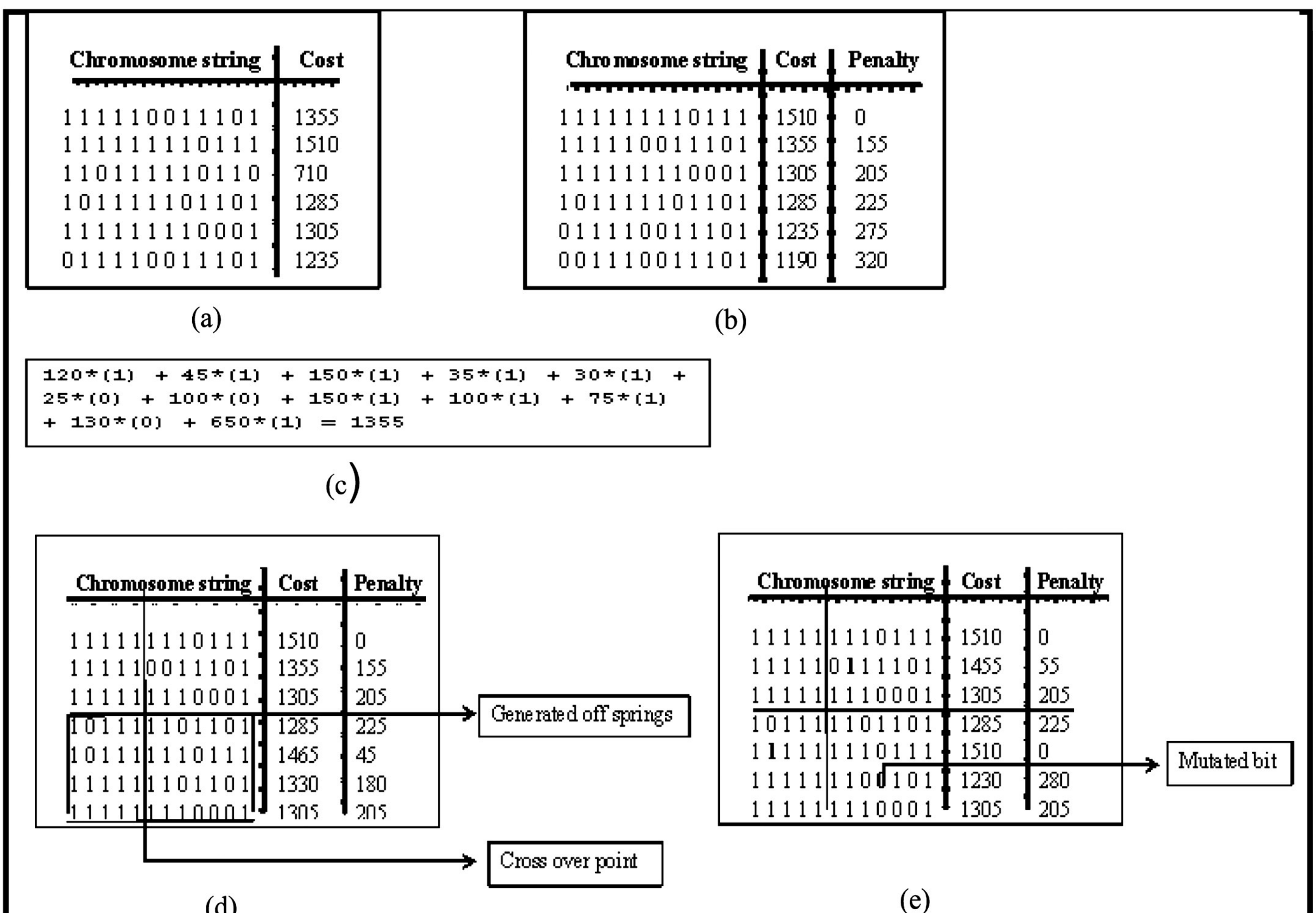
Table 4
Priority matrix for the load manager.

Load	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
points	**1–4**	**5–6**	**7–8**	**9**	**10–15**	**16–18**	**19–20**	**21–24**
L1	1	1	1	1	1	1	1	1
L2	1	1	1	1	1	1	1	1
L3	0	0	0	0	1	0	0	0
L4	1	1	0	0	0	0	0	1
L5	0	0	0	0	0	1	0	0
L6	0	0	0	1	0	0	0	0
L7	0	0	1	0	0	0	1	0
L8	0	1	0	0	0	0	0	0
Total demand (W)	1420	2220	2110	1710	1360	1610	2110	1420

and insufficient supply of energy. A daily load discrimination profile (Table 3) earlier established is then further classified as the priority matrix as shown in Table 4. Following the priority matrix for the respective time of the day, MMIGA is used to intelligently evolve a sequence of bits (shown in Table 5a), which will be implemented by the hardware while observing the following:

(i) Total load demand (P_{dk}) must not exceed available supply (P_{sk}) (under the sufficient energy scenario).

Table 5
Sequence of bits (a) population matrix, (b) ranked fitness table, (c) chromosomes cost computation, (d) description of sample crossover and elitism, and (e) description of sample mutation.



(a)

Chromosome string	Cost
1 1 1 1 1 0 0 1 1 1 0 1	1355
1 1 1 1 1 1 1 1 0 1 1 1	1510
1 1 0 1 1 1 1 1 0 1 1 0	710
1 0 1 1 1 1 1 0 1 1 0 1	1285
1 1 1 1 1 1 1 1 0 0 0 1	1305
0 1 1 1 1 0 0 1 1 1 0 1	1235

(b)

Chromosome string	Cost	Penalty
1 1 1 1 1 1 1 1 0 1 1 1	1510	0
1 1 1 1 1 0 0 1 1 1 0 1	1355	155
1 1 1 1 1 1 1 1 0 0 0 1	1305	205
1 0 1 1 1 1 1 0 1 1 0 1	1285	225
0 1 1 1 1 0 0 1 1 1 0 1	1235	275
0 0 1 1 1 0 0 1 1 1 0 1	1190	320

(c)

120*(1) + 45*(1) + 150*(1) + 35*(1) + 30*(1) + 25*(0) + 100*(0) + 150*(1) + 100*(1) + 75*(1) + 130*(0) + 650*(1) = 1355

(d)

Chromosome string	Cost	Penalty
1 1 1 1 1 1 1 1 0 1 1 1	1510	0
1 1 1 1 1 0 0 1 1 1 0 1	1355	155
1 1 1 1 1 1 1 1 0 0 0 1	1305	205
1 0 1 1 1 1 1 0 1 1 0 1	1285	225
1 0 1 1 1 1 1 1 0 1 1 1	1465	45
1 1 1 1 1 1 1 0 1 1 0 1	1330	180
1 1 1 1 1 1 1 1 0 0 0 1	1305	205

Generated off springs
Cross over point

(e)

Chromosome string	Cost	Penalty
1 1 1 1 1 1 1 1 0 1 1 1	1510	0
1 1 1 1 1 0 1 1 1 1 0 1	1455	55
1 1 1 1 1 1 1 1 0 0 0 1	1305	205
1 0 1 1 1 1 1 0 1 1 0 1	1285	225
1 1 1 1 1 1 1 1 0 1 1 1	1510	0
1 1 1 1 1 1 1 0 0 1 0 1	1230	280
1 1 1 1 1 1 1 1 0 0 0 1	1305	205

Mutated bit

Table 6
Sufficient power allocation for Hours 3–7.

Hour	Active load point	Number of sub-load points	Sub-load point status (1—active; 0—inactive)	Real-time demand (W)	Allocation (W)	Deficit (W)
3	L1	7	120(1) 45(1) 150(1) 35(1) 30(1) 25(0) 100(1)	1420	1395	25
	L2	4	150(1) 100(1) 75(1) 130(1)			
	L4	4	90(1) 45(1) 125(1) 200(1)			
4	L1	7	120(1) 45(1) 150(1) 35(1) 30(1) 25(1) 100(1)	1420	1420	0
	L2	4	150(1) 100(1) 75(1) 130(1)			
	L4	4	90(1) 45(1) 125(1) 200(1)			
5	L1	7	120(1) 45(0) 150(1) 35(1) 30(1) 25(1) 100(1)	2220	2175	45
	L2	4	150(1) 100(1) 75(1) 130(1)			
	L4	4	90(1) 45(1) 125(1) 200(1)			
	L8	1	800(1)			
6	L1	7	120(1) 45(1) 150(1) 35(0) 30(1) 25(1) 100(1)	2220	2185	35
	L2	4	150(1) 100(1) 75(1) 130(1)			
	L4	4	90(1) 45(1) 125(1) 200(1)			
	L8	1	800(1)			
7	L1	7	120(1) 45(1) 150(1) 35(1) 30(1) 25(1) 100(1)	2110	2110	0
	L2	4	150(1) 100(1) 75(1) 130(1)			
	L7	2	300(1) 850(1)			

If i represents the index of each load point, m the number of load points, j the index of each sub-load point and n the number of sub-load points, then the objective function is formulated as follows:

$$\text{Minimize sub—load point allocation} \sum_{j=1}^{n} [S_u(\cdot)],$$

$$\text{Minimize load point allocation} = \sum_{i=1}^{m} [L_u(\cdot)],$$

where S_u (.) is the sub-load point unit j turned on for load point i and L_u (.) is the respective load point unit i turned on.
Subject to

(1) $\sum_{j=1}^{n} [S_u(.)] \leq L_u(.)\ for\ every\ respective\ i$

(2) If P_{sk} is the available supply power for the kth hour, then $\sum_{i=1}^{m}\sum_{j=1}^{n} [S_u(.)] \leq P_{sk}$

(3) If P_{dk} is the present demand power for the kth hour, then $\sum_{i=1}^{m}\sum_{j=1}^{n} [S_u(.)] \leq P_{dk}$

Hence,

$$P_{dk} \leq P_{sk}$$

(ii) Total load allocated must not exceed present demand
If P_{sk} is insufficient, i.e.

$$P_{sk} \leq P_{dk}$$

where P_{ak} is the allocated cumulative load for the kth hour; Optimize sub-load, S_u (.), and load points L_u (.) such that

$$P_{sk} - P_{ak} \approx \in^{+}$$

Such that

$$\in^{+} \rightarrow 0$$

Hence,

$$\left(P_{sk} - \sum_{i=1}^{m}\sum_{j=1}^{n} [S_u(.)]\right) \approx \in^{+}$$

Table 7
Insufficient power allocation for Hours 3–7.

Hour	Active load point	Number of sub-load points	Sub-load point status (1—active; 0—inactive)	Real-time demand (W)	Available supply (W)	Allocation (W)
3	L1	7	120(1) 45(1) 150(1) 35(1) 30(1) 25(0) 100(1)	1420	1326	1320
	L2	4	150(1) 100(1) 75(0) 130(1)			
	L4	4	90(1) 45(1) 125(1) 200(1)			
4	L1	7	120(1) 45(0) 150(1) 35(1) 30(0) 25(0) 100(1)	1420	1245	1245
	L2	4	150(1) 100(1) 75(0) 130(1)			
	L4	4	90(1) 45(1) 125(1) 200(1)			
5	L1	7	120(0) 45(1) 150(1) 35(1) 30(1) 25(1) 100(1)	2220	2100	2100
	L2	4	150(1) 100(1) 75(1) 130(1)			
	L4	4	90(1) 45(1) 125(1) 200(1)			
	L8	1	800(1)			
6	L1	7	120(1) 45(1) 150(1) 35(1) 30(1) 25(1) 100(1)	2220	2098	2090
	L2	4	150(1) 100(1) 75(1) 130(0)			
	L4	4	90(1) 45(1) 125(1) 200(1)			
	L8	1	800(1)			
7	L1	7	120(1) 45(1) 150(1) 35(1) 30(0) 25(0) 100(1)	2110	1980	1980
	L2	4	150(1) 100(1) 75(0) 130(1)			
	L7	2	300(1) 850(1)			

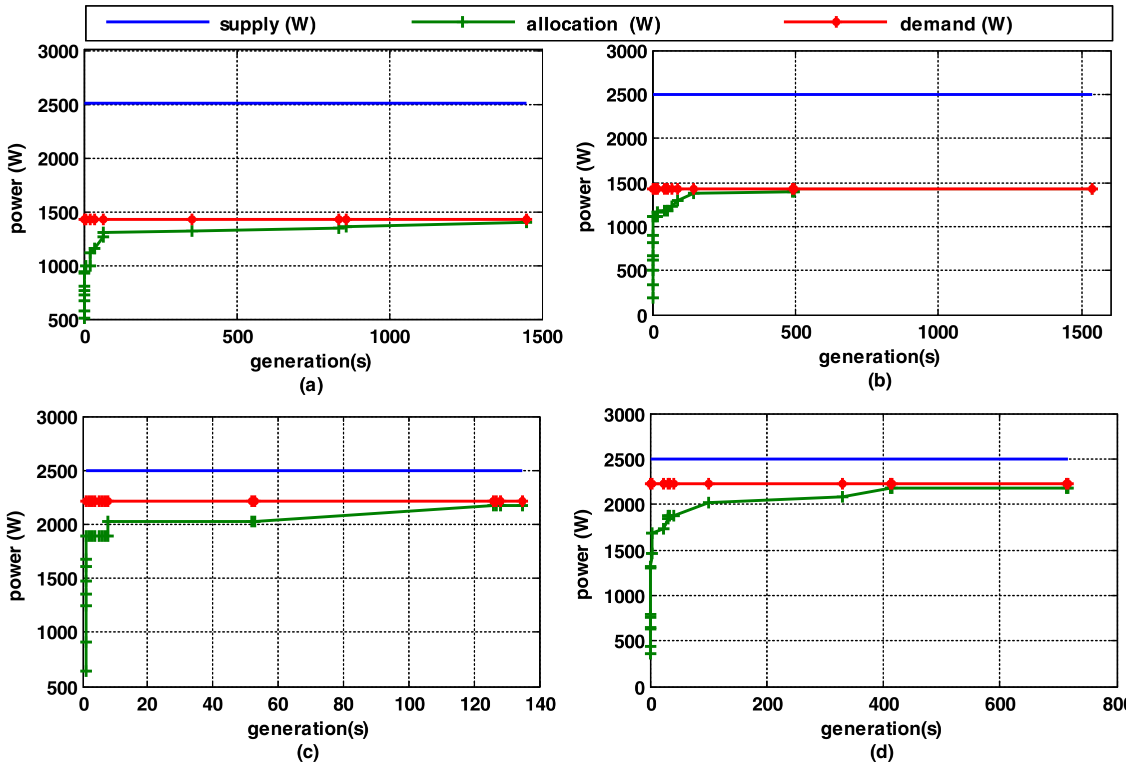


Fig. 3. Load supply, demand and allocation in the sufficient energy scenario for (a) Hour 3, (b) Hour 4, (c) Hour 5 and (d) Hour 6.

(iii) The order or criticality of the sub-division load points is not considered in the limited case scenario.
(iv) Selected or implemented result best matches the ideal value.

Methodology

The proposed MMIGA is a variant of the mild intrusive genetic algorithm as used in Adewumi et al. (2014). The choice of the proposed algorithm stems from the application of the underlying principles of GA in other similar problems due to its speed, flexibility and efficiency offered. A detailed description of the MMIGA as applied to the current problem is presented in the next subsection.

MMIGA

MMIGA is used in arriving at optimal solutions for the load allocation under sufficient and insufficient power supply. As a variant of the MIGA, the modifications are:

1. The length (number of columns) of the population matrix is dynamic (not fixed).
2. The binary bits generated are only used in determining the respective sub-load points to turn on and not to compute penalty (as used in the MIGA).
3. The penalty computation is done as shown in Table 5c where the products of a binary bit and its corresponding sub-load point value are summed up over the length of the matrix.

The MMIGA was designed as a modified population-based approach. Table 5 provides a sample space that illustrates the environment for the activities of MMIGA. GA allows for various ways of defining the population structure (chromosome) (Ozturk and Yildiz, 2006). This MMIGA for this problem uses the binary representation. The steps involve in the MMIGA including that of selection, crossover, elitism and mutation are illustrated in Table 5(a–e). Each chromosome string corresponds to a solution whose fitness is tested for optimality as shown in Table 5b (fitness value of zero).

Results and discussion

The proposed MMIGA algorithm was utilized to run a test on the load of the typical residential house for Hours 3 to 7. The behavior of the algorithm in optimizing the allocation of loads in both sufficient (suff.) and insufficient (insuff.) power scenarios is presented in Tables 6 and 7 respectively. The sufficient power scenario represents a situation in which the real-time supply exceeds the maximum real-time demand, while the insufficient scenario is otherwise. In this paper, the sufficient power is taken as when the available supply is up to 2.5 kVA while the insufficient power is taken as when the available supply is less than 2.5 kVA.

It is easily observed from Table 6 that the active load points and number of sub-active load points for Hour 3 are L1 (7), L2 (4) and L4 (4) respectively with a combined real-time demand of about 1420 W. An allocation of about 1395 W (which represents 98.24%) with a deficit of about 25 W (L1 sub 6) was achieved. Similarly, in Table 6, the active and sub-active load points for Hour 4 are L1 (7), L2 (4) and L4 (4) respectively, with a combined demand of about 1420 W and an achieved allocation of about 1420 W (which represent 100% allocation). In this hour no deficit was obtained as all load requirements were met. Hour 5 also has active and sub-active load points as L1 (7), L2 (4), L4 (4) and L8 (1) with a combined demand of about 2220 W. An allocation of 2175 W (97.97%) with a deficit of 45 W (L1 sub 1) was also achieved. Hour 6 has similar active and sub-active load points as Hour 5, with a combined demand of about 2220 W. An allocation of about 2185 W (98.42%) was achieved with a deficit of about 35 W (L1 sub 4). Differing from preceding hours is Hour 7 with active and sub-active load points to be L1 (7), L2 (4) and L7 (2) and a combined demand of about 2110 W. An allocation of about 2110 W (100%) was achieved with no deficit.

The supply, demand and optimally allocated power for Hours 3–7, using MMIGA is depicted in Fig. 3(a–d) for sufficient power scenario,

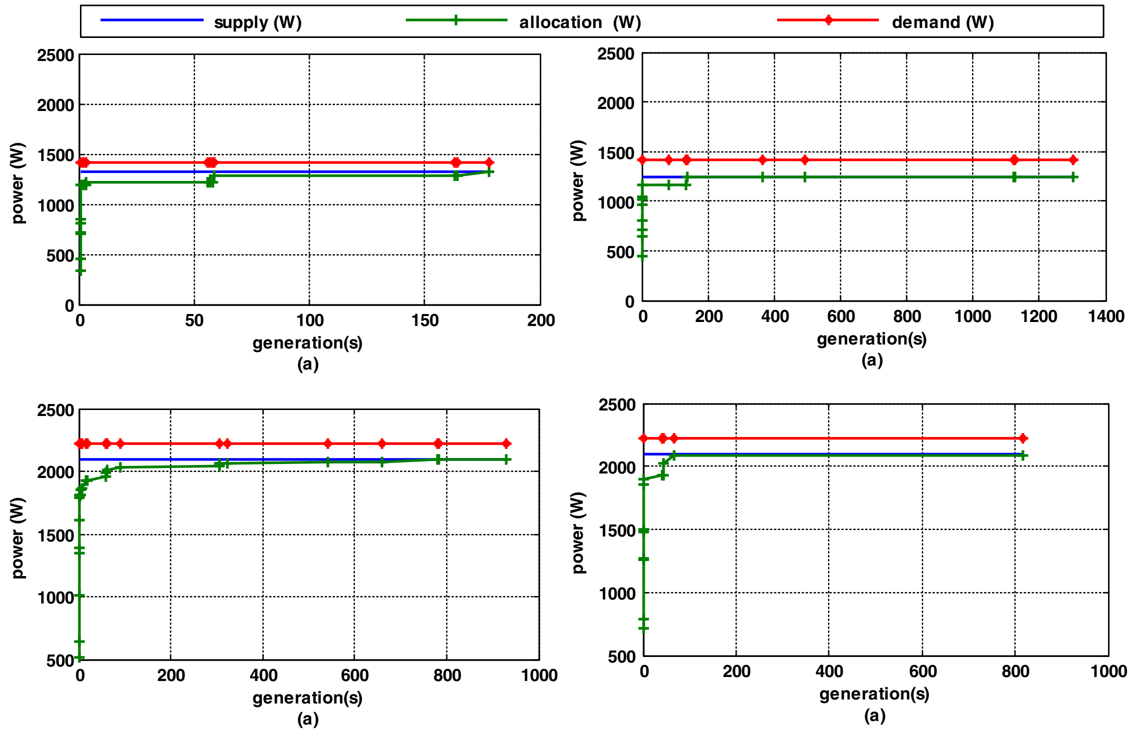


Fig. 4. Load supply, demand and allocation in the insufficient energy scenario for (a) Hour 3, (b) Hour 4, (c) Hour 5 and (d) Hour 6.

and in Fig. 4(a–d) for insufficient power scenario. The figures also reveal the generation at which the best solution was achieved. For example, in Fig. 3a, the optimal power allocation for Hour 3 under sufficient power scenario was achieved at the 1450th generation.

The red lines (stared) in Figs. 3 and 4 denote the real-time demand of the active and sub-active load points (in Watts), while the blue line (unmarked) denotes the real time available supply which in the sufficient case scenario is about 2.5 kVA and the green line (crossed) denotes the allocation that was achieved by the MMIGA in the scenario considered. An average allocation of about 98.99% was achieved in the sufficient energy case scenario by the MMIGA with sub-active deficit points peculiar to L1. The figures thus displayed in Fig. 3(a–e) show the marked ability of the green line in matching the red line since supply in real time exceeds the demand. Also worthy of note is the fact that the objective functions and constraints earlier formulated are fully met by the MMIGA especially in allocation not exceeding demand or available supply.

The behavior of the MMIGA under the insufficiency case scenario was meant to further exhibit the intelligence of the MMIGA as a stochastic tool to intelligently and smartly allocate available scarce resource (in this case, insufficient power) within the available demand rather than just as a binary allocator. The allocations under insufficient energy scenario, for Hours 3–7 are displayed in Table 7. The active load points and sub-active load points for Hour 3 have a real-time demand of about 1420 W with the respective allocation as L1 (7), L2 (4) and L4 (4). Real-time supply was about 1326 W for the hour while allocation was about 1320 W (99.55%). A deficit of about 6 W was observed as shown in Table 7. Similarly, Hour 4 with real-time demand, active and sub-active load points similar to Hour 3, has a real-time supply of about 1245 W for the hour with about 1245 W allocated for the hour (100% allocation) as seen in Fig. 2b. Hour 5 with active and sub-active load points as shown in Table 7 and with a real-time demand of about 2220 W for the hour has a 100% allocation as shown in Fig. 4c of about 2100 W (real-time hourly supply). Similarly, Hour 6 with active and sub-active load points as shown in Table 7 and with real-time demand and allocation as shown in Fig. 4d, the MMIGA was able to achieve about 99.62% in terms of allocation. A 100% allocation was achieved for Hour 7 with the real-time available capacity of about 1.98 kW optimally utilized for the entire hour.

A comparison of the MMIGA in allocating or optimizing the available supply to meet the demand in both the sufficient and insufficient case scenario's as shown in Table 8 shows that while about a 98.88% allocation was achieved in the sufficient case scenario, about 99.84% allocation was achieved in the insufficient case scenario. While the sufficient case scenario has been used as a benchmark in standardizing the performance of the MMIGA, its performance in

Table 8
Sufficient case scenario (Suff) and insufficient case scenario (Insuff).

Hour	3		4		5		6		7	
Scenario case	Suff	Insuff	Suff	Insuff	Suff	Insuff	Suff	Insuff	Suff	Insuff
RTD (kWh)	1.42	1.42	1.42	1.42	2.22	2.22	2.22	2.22	2.11	2.11
RTA (kWh)	2.50	1.326	2.50	1.245	2.50	2.100	2.50	2.098	2.50	1.980
Allocation (kWh)	1.395	1.32	1.42	1.245	2.175	2.10	2.185	2.09	2.11	1.98
Deficit (kWh)	0.025	0.006	0.00	0.00	0.045	0.00	0.035	0.008	0.00	0.00
% Allocation	98.24	99.55	100	100	97.97	100	98.42	99.62	100	100
% Avg allocation	98.88	99.84	98.88	99.84	98.88	99.84	98.88	99.84	98.88	99.84

RTD — Real-time demand, RTA — Real-time availability.

the insufficient case scenario has shown that it is best suited for off-grid optimization especially with the fluctuations and irregularity of solar irradiance.

Conclusion

A solution to the issue of economic limitation in the access to the use of renewable energy by residential houses owned by medium income earners, in developing countries has been proposed and closely addressed in this paper.

MMIGA has been extensively used in addressing the load case scenario of the household earlier presented. Two different scenarios (sufficient and insufficient) were considered. The sufficient case scenario was used to standardize the performance of the proposed algorithm in the insufficient case with the MMIGA exceeding allocation performance in the sufficient case.

This proposed algorithm achieved about 99.84% allocation in the insufficient case thus meeting the objective of being cost effective, smart and simple to use. In this paper consumers' preferences have not been taken into consideration, further research work is considering improving the proposed algorithm to accommodate user's preference in term of demand response. Although, a typical household was considered in this paper, the proposed algorithm (MMIGA) can be applied to different load profile conditions. Also, the implementation of the algorithm to hardware for experimentation is ongoing and it shall be reported soon.

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