Modelling an Artificial Intelligence-Based Energy Management for Household in Nigeria

Rabiat Ohunene Ibrahim, Erick Tambo, David Tsuanyo, and Axel Nguedia-Nguedoung

***Abstract*—Sub-Saharan Africa's low access to electricity and high vulnerability to climate change can be anticipated to constrain the region's future human and economic development prospects. The need for energy conservation, especially electricity, is of crucial importance as it is an economic solution to the problem of energy shortage and atmospheric carbon reduction. The role of Artificial intelligence (AI) has also been displayed by researchers in the promotion of energy management. Most of the past literature in the line of energy management strategies proposed various energy management models based on smart grid and smart meter technology, demand side management, home energy management schemes and management based on AI. This paper proposes an AI-based energy management for households in Nigeria. Genetic algorithm was used on smart meter-like data to optimize the energy consumption of households for 24 hours on a weekday and weekend. To achieve this aim, we determine the typical load profile of a mini-grid setting (for household and commercial load profile), develop a simulation of smart meter-like data and develop an energy management system to optimize electricity consumption during a weekday and weekend in a household. We corroborate our theoretical model with numerical results showing the energy (and consumption) saved during these periods. The algorithm will assist electricity consumers in rural communities to effectively manage their usage by avoiding wastage and the unnecessary payment for energy waste.**

***Index Terms*—Energy management, mini-grid, sub-saharan Africa, artificial intelligence, smart system.**

I. Introduction

AMONG the major concerns and pressing issues in the world today is the issue of energy security and access, energy efficiency as well as energy conservation. The demand for energy is on a constant increase as the world population and consumption is growing rapidly [1]. Energy has been an essential commodity right before the period when mankind worked with stones and sticks to this modern era of rapid industrialization. The last decade of the 20th century to the beginning of the 21st century marks a period of rapid increase in the world energy consumption at a rate of 151% [2], [3].

The population growth of Africa stands among the fastest and youngest in the world. In fact, according to Ref. [4], one out of two people in the world population between now and 2040 are more likely to be African. It is a well-known fact that access to a reliable energy system is very crucial to sustainable development of a nation [5], [6]. Energy is required for the development of many other sectors such as agriculture, health, transportation, housing and so on. Access to reliable and sustainable energy can improve the economy of a country while also providing job opportunities for its citizens. However, in Africa, despite the rapid increase in population and demand for energy, there is still a huge deficit of energy access especially in the Sub-Saharan region of the continent. The continent is plagued with persisting low access to electricity and clean cooking fuel which has a negative effect on development. According to a report [4] on Africa's energy outlook, up to 600 million people have no access to electricity and 900 million people lack access to clean cooking fuel. A Lot of efforts being put in place to combat this energy deficit is still outpaced by population growth. Attention is majorly focused on the urban region because of remoteness and thus cost of extending electricity to the rural settlements. Consequently, only about 1% of the rural population in some Sub-Saharan African (SSA) countries (for example South Sudan, D. R. of the Congo, Chad, Central African Republic, Guinea, Niger, Mauritania, Burkina Faso) have access to electricity [7]. It is estimated that by 2030, about 530million people will still lack access to electricity with nearly a billion lacking access to clean cooking oil in Africa [4]. The heat of Africa's energy setback is more pronounced in Sub-Saharan Africa where the electrification rate grows at a slower pace compared to the rest of the world. Africa is home to an overwhelming amount of energy resources both conventional (fossil fuel) and renewable energy sources (Solar, Wind, Biomass, Geothermal and Hydro). Fossil fuels which are the major source of energy supply are characterized with two major problems. First is the adverse effect these energy sources have on the environment which is the release of carbon dioxide gases into the atmosphere thereby causing global warming [8].

The second problem is the depletion of these energy resources with time due to their non-renewability within a human life-time frame. The consequences of this is an increase in the cost of energy with time which will result in a gradual increase in the energy cost allocation in the residential and commercial building budget [8]. Hence there

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is a need for increase in investment in the area of renewable energy to complement the supply from conventional sources. Furthermore, it is essential to upgrade the power sector by investing more on projects such as grid extension, grid densification, mini-grids and standalone systems in order to meet the exploding increase in electricity demand with time. The conventional grid systems in SSA face a major setback like unreliability, high electrical tariff, poor support for incorporation of renewable energy sources, frequent blackout and brownout due to grid overload and high cost of reaching rural settlements in remote areas. To reach out and meet the electricity needs of these areas, the best solution is decentralized energy technology [9], such as Mini-grids, Micro-grids and Standalone energy systems.

Mini-grids system a potential solution of electricity access for settlements cut out from the reach of the central grid system. The mini-grid system has the ability to be powered by hybrid energy sources such as renewable energy sources with the diesel engine as standby power supply. With the decreasing cost of Solar PV technology and storage systems, the adoption of mini-grid systems for rural areas has started gaining momentum although the cost is still high [9].The need for energy conservation, especially electricity, is of crucial importance as it is an economic solution to the problem of energy shortage and atmospheric carbon reduction. Buildings have been identified among the top largest world energy consumption accounting for up to 40% [10] and in order to maximize energy conservation, there is a need to put in place an effective energy management strategy. World electricity production highly depends on burning fossil fuel which releases a lot of greenhouse gases which are harmful to the atmosphere. In 2014, 67% of world electricity production source was from fossil fuel [11]. It is acceptable when we use limited amounts of electricity to fulfill our convenience, however, excess consumption and wastage of electricity becomes a major issue. People usually find themselves in a situation such as being in a hurry to leave the house and forget to turn off the lights, fan or other appliances. Other cases may be forgetting to put off appliances or putting them on standby when going to bed or just being indifferent about the status of appliances, be it on when not in use or not. These actions may seem harmless but they are a major source of electricity wastage in the average household [12]. It is important to know that, be it in a hurry, forgetfulness or indifferent, these actions will weigh heavily on one's wallet.

Motivated by the works of [7], [9], [5], [13], [14], [15], [3], [2], [16], [17], [18], [38], [39], [40], the aim of this paper is to model an automated system working with the principle of artificial intelligence that can reduce power consumption cost at household level as well as household peak demand. In order to achieve this aim we set the following objectives:

- Obtain typical load profile of a mini-grid setting (household and commercial load profile)
- develop a simulation of smart meter-like data
- Propose an energy management system to optimize electricity consumption during a weekday and weekend in a household.

II. Review on Energy Management Strategy

This section highlighted some of the previous literature on energy management strategy.

A. Technologies for Energy management

Deployment of smart metering systems has already commenced in countries and data from installed smart meter have already and are still being used for research in countries like Ireland [22], England [3] , United States [19], Denmark [2] and other developed countries. In the case of Africa, the idea of smart grid and smart metering system is majorly at the conceptual stage. Researchers have proposed various smart grid model simulations over time. Mekkaou et al. [20] presented a model simulation of a smart grid integrated with solar/wind energy sources. The advantage of their work was that analysis of active power gives the exact idea to know the range of maximum permissible loads that can be connected to their relevant bus bars. However, the electricity cost was not put into consideration in the work. Mohamed and Ali [18] proposed a model simulation of a smart grid with integrated hybrid renewable energy systems. The experimental result showed that the use of smart grid concept will reduce the component size and the cost of generated energy compared to the case without dividing the loads. Krystian et al. [19] proposed a Meters to Models scheme to control energy use at home using smart meter data to predict and control home energy use. Rao et al. [21] made a model simulation of an automatic Meter Reading System for Smart Metering by using ASK/OOK Modulation in Rural Smart Micro-grids. The ASK/OOK system which focuses on transmitting and receiving the measured data of multiple smart meters in smart micro-grid systems by using power line communication (PLC) was simulated. Their findings showed that the present ASK/OOK modem is very simple, economical and has the ability to control the data transmission for smart micro-grid.

Eunice et al. [17] examined the potential of a smart microgrid for off-grid rural electrification in Nigeria. A combination of design thinking and model-based design methodology was employed to select a suitable microgrid configuration and to develop a smart microgrid model. A system consisting of a solar photovoltaic array, battery energy storage and a diesel generator is selected, and the model is developed in Simulink. The proposed smart microgrid was found to be more suitable for off-grid rural electrification in Nigeria than diesel generators which are currently used for off-grid electrification in Nigeria. Refs. [23], [24] studied past literature and gave a comprehensive survey on the internet of things-based energy management in smart cities. Ref. [25] proposed an energy saving system using solar photovoltaic with wireless sensor network. Based on the result obtained, the proposed system demonstrated its superiority over other traditional methods. In Ref. [26], an Internet of things (IoT)-based energy management system which is based on an edge computing framework with deep reinforcement learn- ing was proposed. The energy scheduling scheme; deep reinforcement learning, was analyzed based on "with" or "without" energy servers. It was observed that the proposed method achieved low energy cost while causing lower delay.

B. Demand Side Management (DSM)

The demand side management involves the reduction of energy wastage by monitoring and controlling the consumption behavior of the consumer side of the unit to ensure more efficient system operation, lowering the electricity bill at the consumer side and reduction of peak demand all day through. Some authors (see [13], [27]) identified the DSM scheme as the strategy to tackle the problem of demand and supply balance especially considering the fact that increasing demand is accompanied with limited fuel resources. The methods by which a DSM scheme can be achieved are discussed in [13], [28]. Ref. [29] reviewed several DSM techniques and Algorithms, which two DSM models were compared to show the performance based on cost minimization, voltage fluctuation and system power loss. Their result showed the importance of balance between objectives such as electricity cost minimization, peak load occurrence, and voltage fluctuation evolution while simultaneously optimizing the cost. Barbato et. al. [30] worked on a distributed DSM framework for the smart grid where the DSM was designed to reduce peak demand by applying a dynamic pricing system which is a function of the consumer total power demand. The appliances were controlled based on scheduling methods. The proposed system was able to decrease the capital expenditure required to meet increasing demand on the grid system. Puttamadappa and Parameshachari [31] proposed a methodology which performed a DSM in smart grids of households which has the energy storage (battery) and distributed solar photovoltaic generation storage. Non-residential load was considered in their work while their proposed model was able to reduce upto 11.2% of the energy cost.

C. Home Energy Management Scheme (HEMS)

Lujano-Rojas et. al. [32] proposed an optimal load management strategy for residential consumers which utilizes communication infrastructure of the future smart grid system. Their result showed that the proposed model gives way to consumers to control their daily energy consumption as well as adjust their electricity bill according to their economic situation. Zhou et. al. [33] proposed a binary particle swarm optimization as an energy management technique in adjusting the appliance usage. In [34], a smart home energy management system with a multilayer structure which is the interface, control and load layer is designed. An optimal scheduling model for the SHEM was constructed while a fusion of harmony search algorithm and the particle swarm algorithm was used to solve the model. Their result showed an effective improvement in the load curve as well as a reduction in the electricity cost. Ref. [2] developed a home energy management system that utilized machine learning in order to reduce energy. Their result showed an energy reduction potential but more data will be required to run a real test involving automated control of the devices. Some researchers (see [28], [35]) were able to propose a HEMS scheme that put into consideration the comfort of the consumer while ensuring optimization of energy.

D. Artificial Intelligence-based Energy Management

Artificial Intelligence-based solutions have been shown by different literatures to prevail in the automation, control and management of energy consumption from home to the grid level. Elkazaz et. al. [36], proposed an automated control technique (using genetic algorithm) for optimizing the operational performance of the DG units within the residential applications. Their result showed a significant decrease in the daily household consumption cost. Jo and Yoon [15] proposed three intelligent models as IoT platform application services for a smart home. Having identified the challenges associated with managing smart home devices with separate IoT platforms as network congestion and energy wastage, the proposed models were able to address these challenges as demonstrated in their work. Deployment of smart grid systems and smart homes in- volves connection of IoT and other intelligence devices such as sensors and smart meters that are capable of generating large flows of data. These data create a suitable platform for AI to predict load network, user consumption habits and drawing an accurate user consumption pattern for each energy user [37]. Ref. [1] argued that energy prediction in buildings contributes significantly to global energy saving, though review of AI based previous work.

Having reviewed past works related energy management strategies, it was observed that many literatures proposed various energy management models based on smart grid and smart meter technology, demand side management, home energy management schemes and management based on Artificial Intelligence. However, the majority of these proposed mod- els were focused on the urban regions mostly in developed countries. There is very little literature focusing on energy management model strategy based on Artificial intelligence.

III. Methodology

A. Notations

- C_m: Represent the consumers connected to the mini-grid where $m = 1, 2, \ldots, k$, is the number of consumers.
- x_i: are the appliances in the home, where $i = 1, 2, \ldots, J$
- x_i^h and x_i^l: are the high priority and low priority appliances classification, respectively.
- $P_{x_i}^r$: is the rated power of appliance x_i
- $P_{x_i}^c$: is the power consumption of appliance x_i
- t_{x_i}: is the number of working hours of appliance x_i
- Z_{x_i}: is the working status of appliance x_i following the rule;
- $Z_{x_i} = 1$ iff x_i is on and 0 otherwise
- $P_{T_n}^a$: is the available power at period T_n
- $P_{T_n}^c$: is the power consumption at period T_n, where $P_{T_n}^c = \sum P_{x_i}^c$
- $U_{T_n}^{C_m}$: is the upper power consumption threshold at period T_n set by consumer m.
- $L_{T_n}^{c_m}$: is the lower power consumption threshold at period T_n set by consumer m.
- E^m: is the total energy consumed by each consumers connected to the mini-grid over a given period of time.

- E^m_{cost}: is the total cost of energy used by consumer over a given period of time.
- U_{x_i}: is the Upper power consumption for appliance i.
- L_{x_i}: is the lower power consumption for appliance i.
- R: Unit price of electricity

B. Mathematical formulation of the model

Starting with the objective function (1) which minimizes the total consumption cost of a consumer;

$$min \sum_{i=1}^{J} P^c_{x_i} t_{x_i} R \tag{1}$$

Subjected to:

$$U^{C_m}_{T_n} < P^a_{T_n} \tag{2}$$

Where (2) which shows that the upper power consumption threshold set by any consumer should be strictly less than the available power, must be satisfied at all times.

$$\sum P^c_{x_i} < U^{C_m}_{T_n} \quad and \quad Z_{x^l_i} = 0 \tag{3}$$

If (3) occurs, then no energy is lost at time period T_n.

$$P^c_{x_i} < L_{x_i} \quad and \quad Z_{x_i} = 0 \tag{4}$$

If (4) satisfied, then an appliance x_i is totally disconnected. On the other hand,

$$P^c_{x_i} < L_{x_i} \;\; and \;\; Z_{x_i} = 1,$$

then the appliance is on standby mode, and should be automatically disconnected.

$$Z_{x_i} \in \{0, 1\} \tag{5}$$

and (5) shows that the integrality constraint.

C. Classification of household

The household is classified into three classes which are based on their income level as follow:

- *Low income class:* This class of people are those earning a monthly income below \$200. They make use of basic appliances necessary for daily activity.
- *Middle income class:* this class earns between \$200 and \$600 in a rural community. Their electrical appliances are assumed to be more than that of the low income earner.
- *High income class:* this class of people are those whose monthly income is above \$600. They are characterized with having the most electrical appliances compared to the middle and low-income classes and thus likely to consume more electricity.

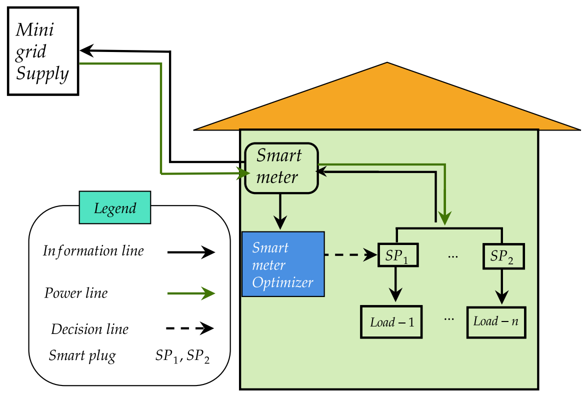

Fig. 1: Model Architecture

D. Simulated Smart System Model Architecture

The architectural presentation of the proposed Energy management system is as presented in Figure 1. The working protocol of the proposed system is enabled by the presence of a smart meter (or prepaid smart meter), smart plugs, loads (in form of electrical appliances) and availability of power generation to the building from a mini-grid or any energy source. The combined system of smart things (smart meter, smart system optimizer and smart plugs) will interact and share information relevant for the optimization process via Internet of Things (IoT) protocol.

E. The Smart system optimizer

This smart system optimizer as we have named it is the brain-box of the energy management model. This system makes use of the embedded algorithm to perform intelligent decision making to either turn off an appliance or let it run. It obtains information such as the power consumption of each appliance and the total consumption per hour from the smart meter, the appliances priority for that hour which has been predefined. The system uses this information to determine the demand limit for that hour and check if the demand limit is exceeded. The system communicates a decision to the smart plug to either switch off a device or not. The working Principle of the Smart System Optimizer is shown in figure 2. The simulation process is mainly in two parts:

1) Appliance Priority: The priority of the appliances is classified broadly into two; high priority (H) or Low priority (L), depending on the hour of the day. A high priority appliance at a particular hour necessary to stay actively working ("on" mode) when the user switches it on. For example, the light bulb is classified as a high priority appliance in the night time while the user is still active but the priority will change at the hour when the user goes to sleep. Also, the refrigerator is classified as a high priority appliance throughout the day as it is necessary for it to stay on to preserve items all day long. On the other hand, any appliance classified as low priority appliances must be turned off if found actively working. These are appliances which the consumer is not necessarily using at that particular hour.

2) Demand Limit: The demand limit at a given hour is defined in this context as the power consumption limit at

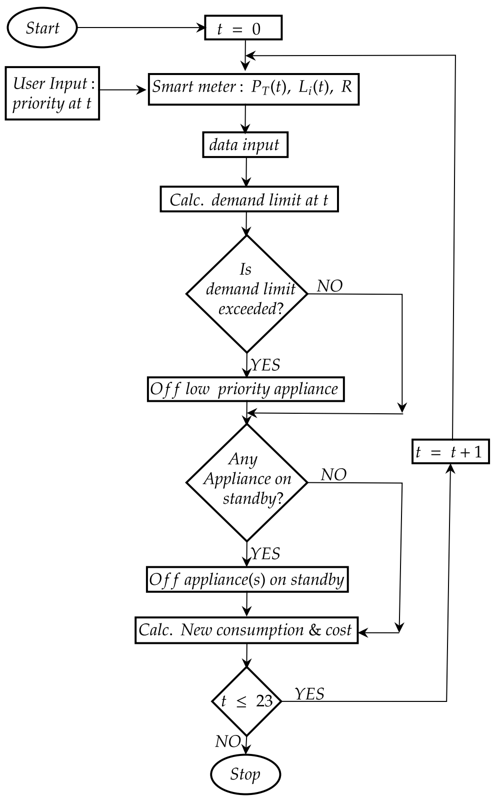

Fig. 2: Flowchart of the smart system optimizer showing it working principle.

that hour. For any given hour, the allowable consumption limit is the total consumption of all high priority appliances at that hour. If this limit is exceeded, it implies that a low priority appliance is activated and in response, the proposed energy management system adjusts the consumption level by turning off appliances of the low priority. Furthermore, the energy management system also ensures that all appliances on standby (both Low and high) are turned “off” . It can be seen that the demand limit setting is directly linked to the priority of the appliance.

IV. Computational Results

A. Data

The data input sample for the simulation process is as displayed in the tables II and III. Table III outlines the appliances power ratings in a fully working situation and in a standby status. Table II indicates the hourly priority of the appliance and the appliances working status (i.e., ON (n), OFF (o) or standby(s)).

The simulation process was implemented in two stages. The first stage is designed to take in inputs of appliances rating (as in table III) and the appliances working status. The algorithm uses this data to simulate the hourly consumption of each appliance, the working status of the appliance and the total hourly consumption. This stage serves as the smart meter data-like input for the simulation. The second stage of the simulation is embedded with an algorithm that takes information output from the first stage simulation (hourly consumption of each appliance, the working status of the appliance and the total hourly consumption), calculates the demand limit at that hour and determines if the demand limit is exceeded.

B. Load profiles

We started by designing appliances count and hours of usage (see figs. 10 and 11). This step is necessary to understand the load profile for each of the three classes of households, the profile of commercial centers and the general or total load profile. The load profile gave insights as to when appliances are being used and when not in use. For instance, fig. 10 shows that between the hours of 9:00 - 15:00, users are not at home during the weekday. However, in fig. 11 the commercial load profile shows that more electricity is consumed during the day.

C. Simulation of appliances for Weekday usage

The aggregate optimization result for both cost and consumption as applied to low income, middle income and high income residential homes is as displayed in figs 3, 4 and 5 respectively.

It was observed that in fig. 3, some appliances that were supposed to be turned off were left on thereby consuming more energy. Our algorithm detected and turned these appliances off. Similarly, figs. 4 and 5 shows the optimized plots for appliance usage in the morning hours. It is interesting to note that, from figs. 3, 4 and 5, usage appears to be high between the hours of $17:00-23:00$. This could be because the household individuals have returned from work and high priority appliances are now turned on, conversely, this is not the case between $10:00-16:00$.

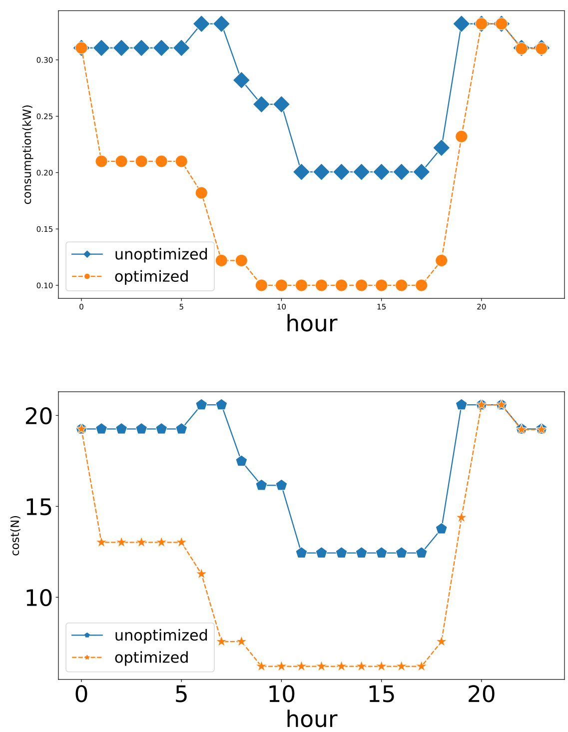

Fig. 3: Aggregate consumption and cost for low income, with the blue-solid and green-dash lines showing unoptimized and optimized states, respectively.

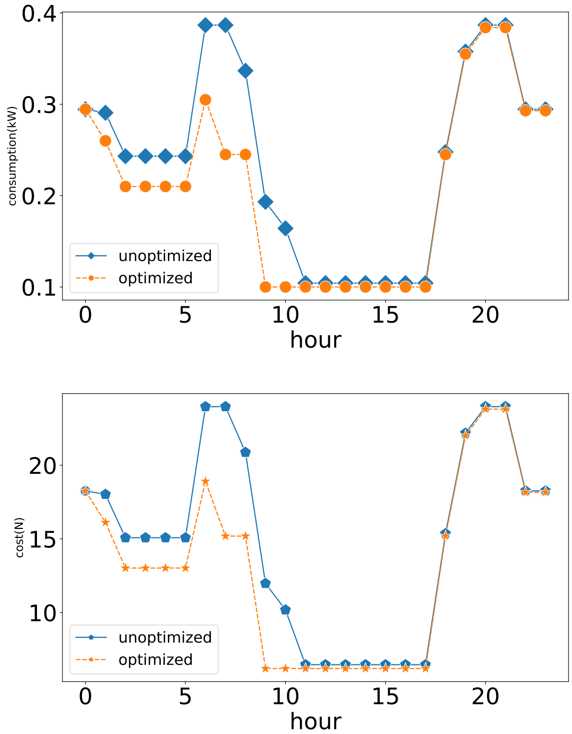

Fig. 4: Aggregate consumption and cost for middle income, with the blue-solid and green-dash lines showing unoptimized and optimized states, respectively.

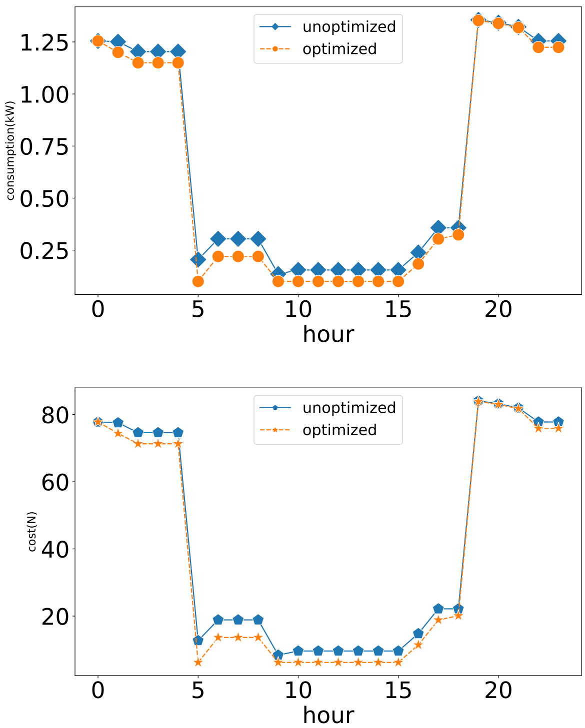

Fig. 5: Aggregate consumption and cost for high income,with the blue-solid and green-dash lines showing unoptimized and optimized states, respectively.

D. Simulation of appliances for Weekend usage

Similarly, the simulation for weekend usage is shown in figs. 6, 7, and 8. It was observed that there was high usage of appliances during the day time, this could be because most users are indoor and using their appliances. Fig 6 shows a sharp increase between 09:00:00 and 10:00:00 because the individual makes use of his washing machine in this period. Also observed from these figs., some low-priority appliances during the day time (such as security light) were turned off and thereby optimizing the consumption and its cost.

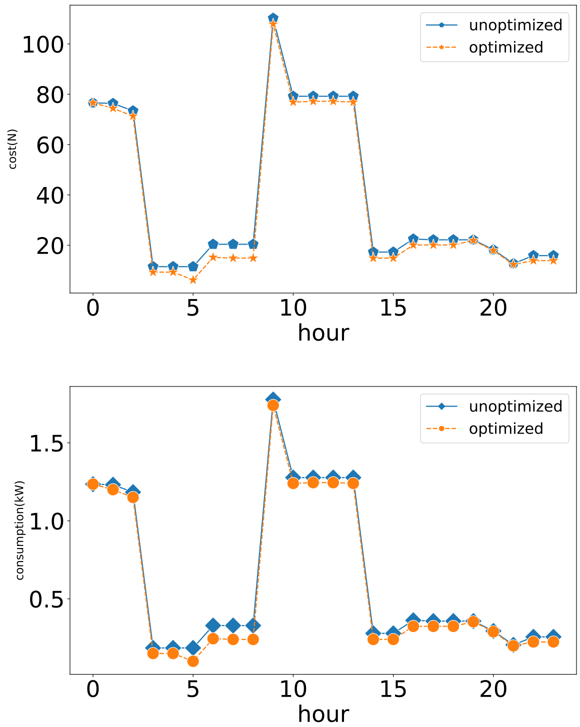

Fig. 6: Aggregate consumption and cost for high income, with the blue-solid and green-dash lines showing unoptimized and optimized states, respectively.

E. Discussion

Having run the simulation for several test cases by varying the data in the input file, we observe that the proposed algorithm for the smart energy management was able to detect and shed a working low priority and standby loads to the off-mode. Observation on each of the household is as follow

- Low-income class : During the weekday, it was observed that there was a large amount of energy wastage between the hours of 03:00 to 16:00 hours as shown in fig. 3. These power wastages were mainly as a result of some low priority appliances (such as fan, security light, TV on standby and incandescent bulb) which were supposed to be put off were left on. The amount of energy used before optimization and after optimization in each hour were also shown in fig. 6.
- Middle-income class : During the weekday, energy was saved during the hours of 00:00 to 11:00. Some low-priority appliances (such as charger and bulbs) were left either on or standby as shown in figs. 4.
- High-income class: Some low-priority appliances (as categorized based on the hour) such as bulb and radio were on instead of off (see fig. 5).

TABLE I: Summary of the results for weekend and weekday

	Weekend									Weekday								
	High			Middle			Low			High			Middle			Low		
	Unopt.	*Opt.*	*gap(%)*	*Unopt.*	*Opt.*	*gap(%)*	*Unopt.*	*Opt.*	*gap(%)*	*Unopt.*	*Opt.*	*gap(%)*	*Unopt.*	*Opt.*	*gap(%)*	*Unopt.*	*Opt.*	*gap(%)*
Consumption	15.08	14.06	6.11	7.01	5.65	19.39	7.76	5.26	32.20	21.01	17.49	16.74	354.81	319.68	9.9	6.57	4.43	32.55
Cost	935.10	877.99	6.11	434.81	350.52	19.39	481.36	326.34	32.20	1302.59	1080.55	16.74	5.72	5.16	9.9	407.60	274.95	32.55

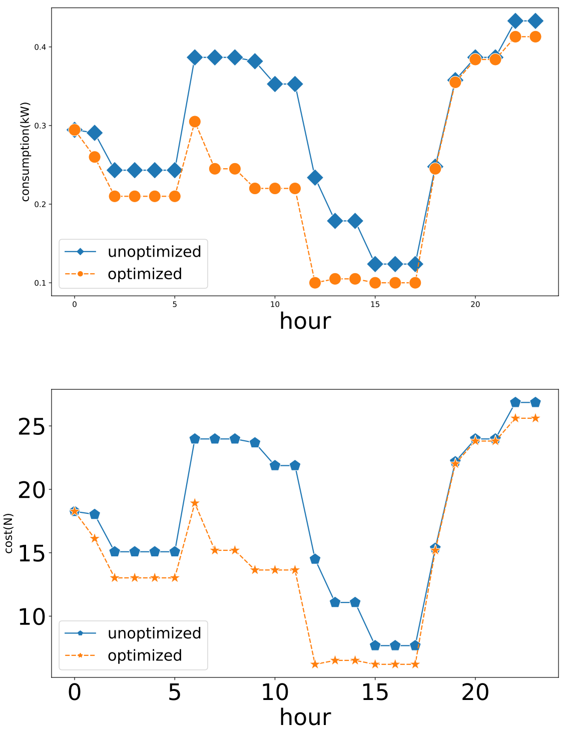

Fig. 7: Aggregate consumption and cost for middle income, with the blue-solid and green-dash lines showing unoptimized and optimized states, respectively.

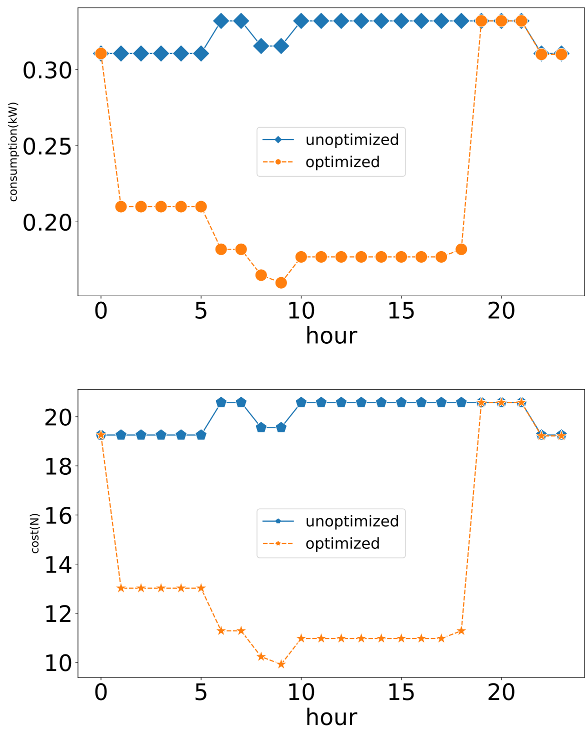

Fig. 8: Aggregate consumption and cost for low income, with the blue-solid and green-dash lines showing unoptimized and optimized states, respectively.

F. Evaluation

Table I shows the aggregate of total energy consumed and its corresponding costs as presented for each household classification. The gap is computed using

$$gap = \frac{Unopt. - Opt.}{Unopt.} \times 100\% \qquad (6)$$

where $Unopt.$, $Opt.$, Consumption and cost represents the value for unoptimized, optimized values, consumption and cost (in Nigerian Naira), respectively. Table I is the total consumption and cost for 24 hours.

Furthermore, the distribution of the consolidated consumption for both weekday and weekend usage as shown in fig. 12 and fig. 9. As expected, during the weekend, there was high consumption for each class during the day. Similarly, for weekdays, low consumption was recorded during the day time. Fig. 9 shows the boxplot distribution of consumptions, the *high income earners* recorded highest consumption, this is due to the presence of more appliances in this class of earners.

V. Conclusion

Among the major concerns and pressing issues in the world today is the issue of energy security and access, energy efficiency as well as energy conservation. The objective of this research is to develop an automated system working with the principle of Artificial intelligence that can reduce power consumption and cost at the household level using simulated data from already existing mini-grid systems and exploring the consumer‘s electricity consumption behavior. We classify the households into three classes; High, Middle and Low income earners. We examine the load profiles for each class of the household usage and the load profile for commercial centres(i.e. schools, hospitals, milling plants, water pumps, and street lights. The simulated data was then simulated based on energy usage on weekdays and weekends. Based on experimental results; the energy (and consumption) saved during the weekday for high, middle and low income earners are 16.74%, 9.9% and 32.55%, respectively. Similarly, the corresponding cost and consumption saved during weekends for high, middle and low income earners are 6.11%, 19.39% and 32.20%, respectively.

It was observed that for low income earners, appliances such as *incandescent bulbs, security light, fan* and *television* were left either on or standby, which consume energy and the smart system turned it off to save energy. For middle income earners, appliances such as *security lights* and *compact fluorescent bulbs* were left on, *laptop* and *phone charger* were left on standby, and these activities also consumed energy

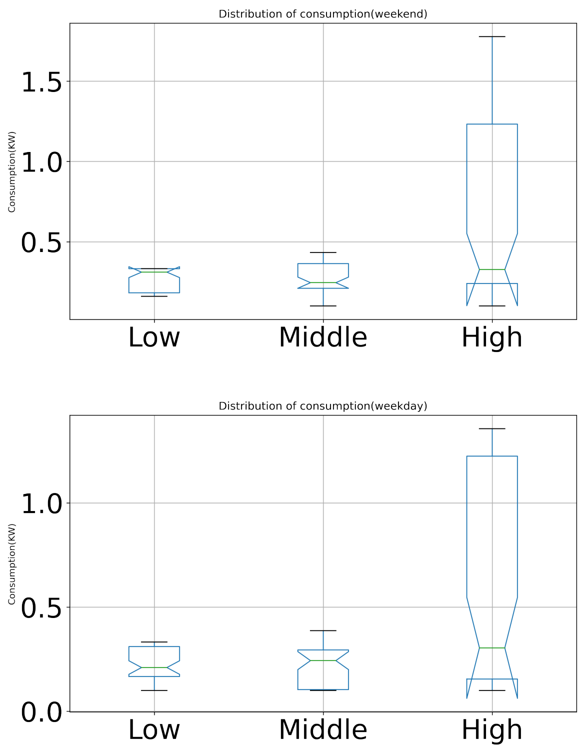

Fig. 9: Boxplot showing distribution of consumption for each household classification. The left and right panels shows each households consumption for a weekend and weekday, respectively.

which the smart system was able to turn off. For high income, *security, TV, compact fluorescent bulbs* were turned on, and some appliances such as *laptop* and *phone charger* were left on standby. The proposed smart system algorithm has displayed a potential for energy management at the household level by cutting off electrical appliances which are not being used but fully consuming electricity as well as appliances on standby. The smart system algorithm will not only help the consumer to reduce electricity cost by reducing consumption but also help to reduce demand at the grid level. The proposed algorithm can serve as a potential energy serving tool in households. The algorithm will assist electricity consumers in rural communities to effectively manage their usage by avoiding wastage and the need to pay for energy waste.

The limitation of this work is the use of simulated data for the modeling which might not always be the case in a real life scenario. In future work, real data will be used for simulations over a six (6) months period.

Code and Data Availability

The code and datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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TABLE II: Appliances priority and working mode per hour
^{L} Low, ^{H} High, ^{n} on, ^{s} standby and ^{O} off

Time	Compact Florescence Bulb	65" LED TV	Refrigerator	Security light	Radio	TV decoder	Laptop Charging	Phone Charging	42" LED TV
00:00	L / n	L / s	H / n	H / n	L / s	L / n	H / n	H / n	L / s
01:00	L / n	L / s	H / n	H / n	L / s	L / n	H / n	L / s	L / s
02:00	L / n	L / s	H / n	H / n	L / s	L / n	L / s	L / s	L / s
03:00	L / n	L / s	H / n	H / n	L / s	L / n	L / s	L / s	L / s
04:00	L / n	L / s	H / n	H / n	L / s	L / n	L / s	L / s	L / s
05:00	L / n	L / s	H / n	L / n	H / s	L / n	L / s	L / s	L / s
06:00	L / n	H / n	H / n	L / n	H / s	H / s	L / s	L / s	H / s
07:00	L / n	H / n	H / n	L / n	H / s	H / s	L / s	L / s	H / s
08:00	L / n	H / n	H / n	L / n	H / s	H / s	L / s	L / s	H / s
09:00	L / n	H / s	H / n	L / o	H / s	H / s	L / s	L / s	L / s
10:00	L / n	H / s	H / n	L / o	H / s	L / n	L / s	L / s	L / s
11:00	L / n	H / s	H / n	L / o	H / s	L / n	L / s	L / s	L / s
12:00	L / n	H / s	H / n	L / o	H / s	L / n	L / s	L / s	L / s
13:00	L / n	H / s	H / n	L / o	H / s	L / n	L / s	L / s	L / s
14:00	L / n	H / s	H / n	L / o	H / s	L / n	L / s	L / s	L / s
15:00	L / n	H / s	H / n	L / o	H / s	L / n	L / s	L / s	L / s
16:00	L / n	H / s	H / n	L / o	H / s	L / n	L / s	L / s	H / n
17:00	L / n	H / n	H / n	L / o	H / s	L / n	L / s	L / s	H / n
18:00	L / n	H / n	H / n	L / o	H / s	H / n	L / s	L / s	H / n
19:00	H / n	H / n	H / n	L / o	H / s	H / n	L / s	L / s	H / n
20:00	H / n	H / n	H / n	H / n	H / s	H / n	L / s	L / s	H / s
21:00	H / n	H / n	H / n	H / n	H / s	H / n	L / s	L / s	H / s
22:00	L / n	H / s	H / n	H / n	H / s	H / n	H / n	H / n	H / s
23:00	L / n	H / s	H / n	H / n	H / s	H / n	H / n	H / n	H / s

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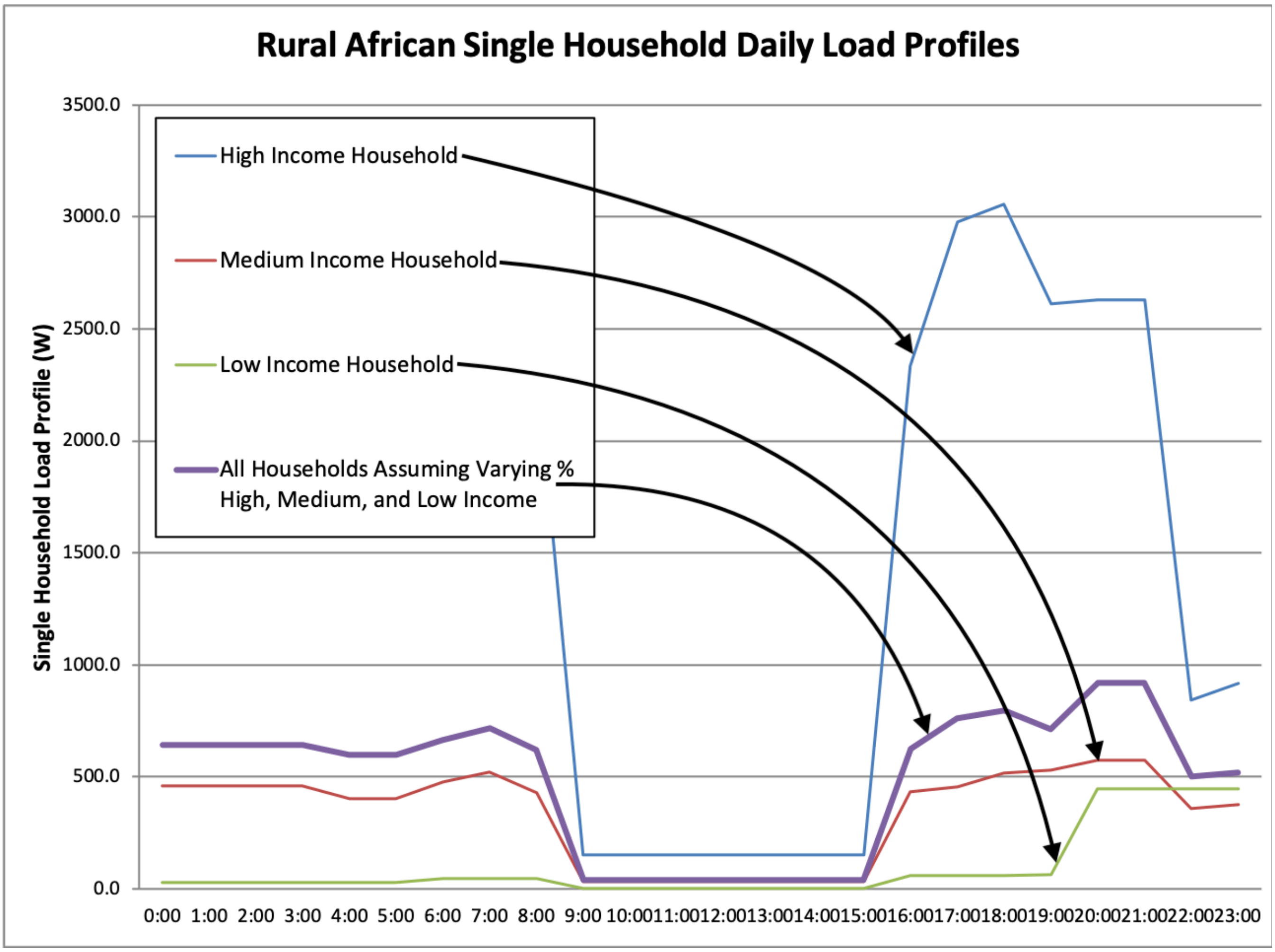

Fig. 10: A single household load profile

TABLE III: Appliance rating

	Appliances Power Ratings		High Income Household	Medium Income Household	Low Income Household
	Appliance Wattage (W)	Appliances Standby Power (W)	Appliance Count	Appliance Count	Appliance Count
APPLIANCES					
Lighting System					
Incandescence bulb	100	0	0	2	4
Compact Florescence Bulb	29	0	5	2	0
Security light	50	0	3	1	0
Entertianment					
22 Inch LED TV	17	0.5	0	1	1
42 Inch LED TV	58	0.3	2	1	0
65 Inch LED TV	120	1	1	1	0
DVD Player	26	0.2	1	1	1
Radio	5	0.1	3	1	1
TV decoder	20	0.4	1	1	1
Thermal Comfort					
Fan	60	0	4	3	2
Air Conditioner	1000	1.5	2	1	0
Refrigerator	100	0	2	1	0
Electric Kettle	1200	0	1	1	0
Microwave	600	3	1	0	0
Other Appliances					
Phone Charging	4	0.2	4	2	1
Laptop Charging	50	2.5	2	1	0
Printer	20	0.1	1	0	0
Washing machine	500	1	1	0	0

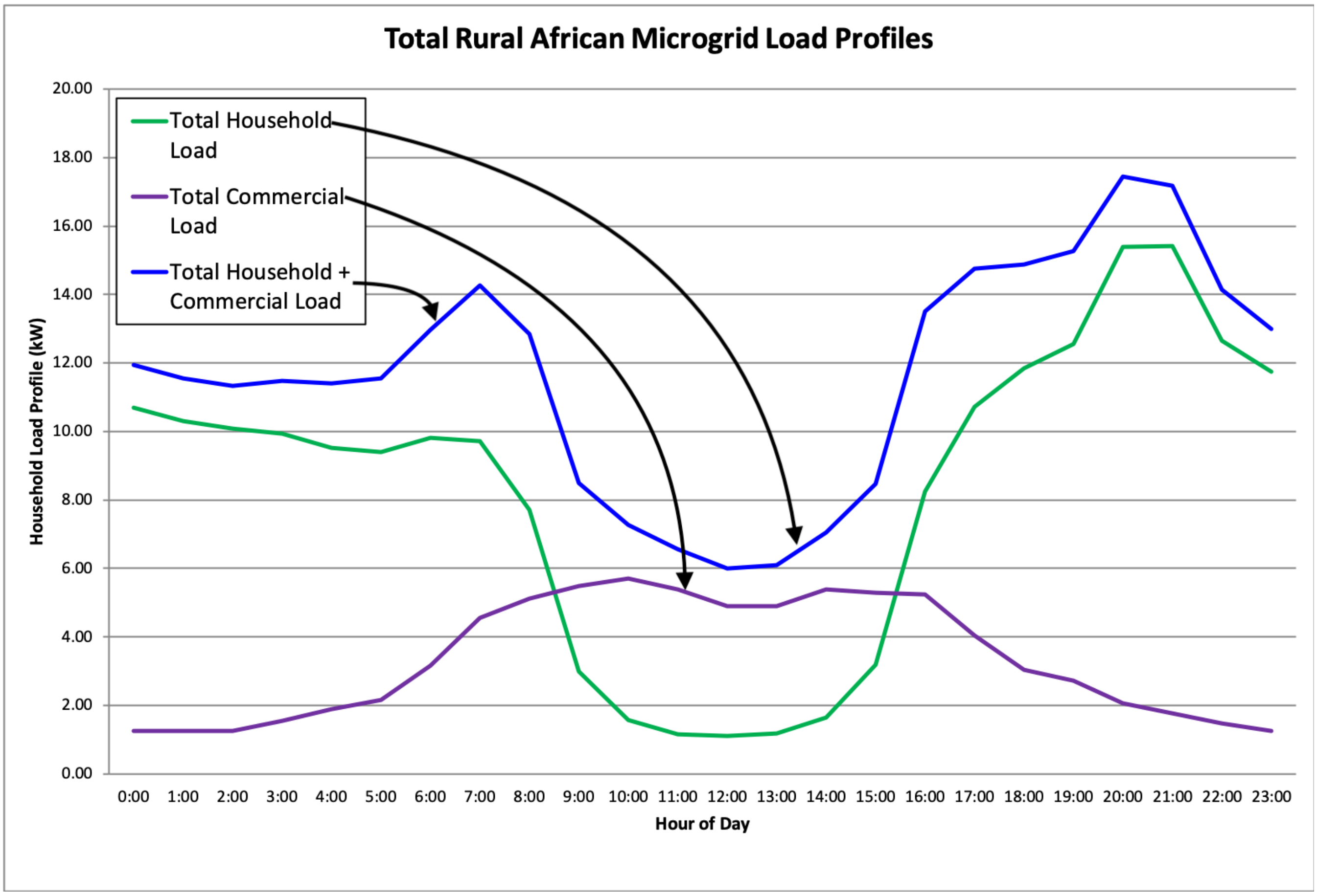

Fig. 11: Global load profile

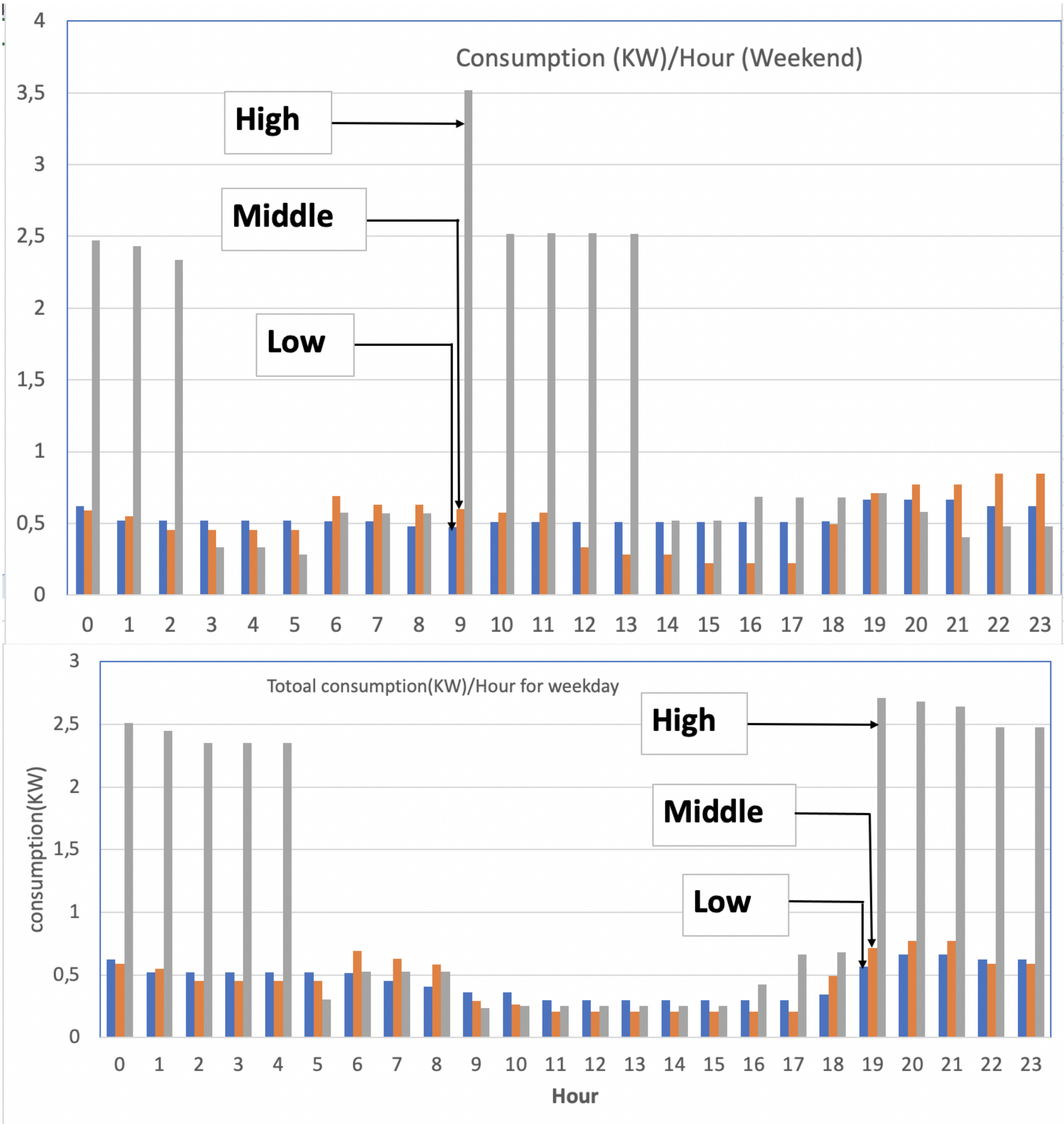

Fig. 12: Effectiveness of the model based on total energy consumption for weekend and weekday with errorbar. Each household classificition are distinguished by colors.