Sustainable Cities and Society 59 (2020) 102235

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Assessment of multiple-based demand response actions for peak residential electricity reduction in Ghana

Felix Amankwah Diawuo[a,b,*], Marriette Sakah[c], Stephane de la Rue du Can[d], Patricia C. Baptista[a], Carlos A. Silva[a]

[a] Center for Innovation, Technology and Policy Research - IN+, Instituto Superior Tecnico, Technical University of Lisbon, Av. Rovisco Pais 1, 1049-001 Lisbon, Portugal
[b] School of Engineering, University of Energy and Natural Resources (UENR), P. O. Box 214, Sunyani, Ghana
[c] Darmstadt Graduate School of Energy Science and Engineering, TU Darmstadt, Germany
[d] Energy Analysis and Environmental Impacts Division, Energy Technologies Area, Lawrence Berkeley National Laboratory, 1 Cyclotron Road, MS 90R2121, Berkeley, CA 94720, USA

ARTICLE INFO

Keywords:
Household survey
end-use electricity monitoring
peak demand
load curve
voluntary demand response

ABSTRACT

Demand-side management initiatives such as voluntary demand response provide significant energy savings in the residential sector, which is a major peak demand contributor. The potential of such savings remains unexplored in Ghanaian households due to insufficient electricity consumption data, lack of end-user behavior information and knowledge about the cost-effectiveness of such programs. This research combines 80 household survey information and energy use monitoring data of household appliances, to assess the residential demand response potential of Ghana. A bottom-up approach based on modified end-use model is used to develop aggregate hourly load curve. The estimated electricity consumption is categorized based on their degree of control to determine peak demand reduction potential for the period 2018-2050. The average daily peak load reduction ranged between 65-406 MW representing 2-14% for the considered scenarios by 2050. The results show appreciable economic viability for investment in demand response with net present value varying between 28-645 million US$. We find that price, energy security and environment signals influence end-users' electricity use behavior. Authors observe that for energy and cost savings to be realized, utility providers and consumers need effective cooperation on information delivery and feedbacks, and consumers should be incentivized to balance the benefits.

1. Introduction

Electricity use for delivery of modern services has increased immensely in recent years. Its demand is anticipated to grow globally and particularly swiftly in developing countries (Saidur, Masjuki, Jamaluddin, & Ahmed, 2007). Global electricity demand is projected to grow at 2.1% per year to 2040 and 4.5-8.5% across African countries within the same period (2019a, IEA, 2019a). In Ghana, demand for electricity has seen a constant rise with average yearly growth of 3.3% between 1990 and 2013 (IEA, 2017), with an upward projection of 6% per year until 2023 (GRIDCo, 2018). Installed supply capacity on the other hand realized a 5.7% average annual growth between 2000 and 2015 (IEA, 2017). In 2017, the system recorded a peak demand of 2,192 MW (GRIDCo, 2018) and an installed capacity of 4,310 MW although only 3,890 MW of this generation capacity was dependable and available for grid utilization (Energy Commission, 2018a). Therefore, while present supply capacity seems technically adequate to meet the peak demand, pockets of power supply shortages frequently occur due primarily to fuel supply constraints (Diawuo, Sakah, Pina, Baptista, & Silva, 2019). Hydropower plants in the generation mix are seasonally faced with variable rainfall patterns while the exogenous nature of fossil-based fuels used in Ghana's thermal power plants poses financial and fuel supply restraints (Sakah, Diawuo, Katzenbach, & Gyamfi, 2017). Historically, Ghana has faced perennial power rationing spanning within the periods 1994, 1997-98, 2006-07 and 2012-16 (Diawuo et al., 2019). Future energy supply is likely to face challenges due to demand growth, energy insecurity and climate change vulnerabilities. Investment in conservative fuel sources and/or supply-side management (SSM) strategies exclusively as a remedy to this challenge is unsustainable in the long run considering global energy market volatilities and uncertainties. Investment and energy policy decisions in power system planning strongly advocate for demand-side management (DSM)

* Corresponding author.
E-mail address: felix.diawuo@tecnico.ulisboa.pt (F.A. Diawuo).

https://doi.org/10.1016/j.scs.2020.102235
Received 2 October 2019; Received in revised form 5 March 2020; Accepted 25 April 2020
Available online 04 May 2020
2210-6707/

as a crucial option or supplement to amplify power generation improvement (De la Rue du Can, Pudleiner, & Pielli, 2018; Ouedraogo, 2017).

The purview of DSM when it was first introduced in the 1980s comprised strategic conservation, customer generation, load management, electrification, new uses and adjustments in market share (Gyamfi, Diawuo, Nyarko Kumi, Sika, & Modjinou, 2018). Spinning reserve, demand response (DR) and Energy efficiency (EE) projects have in recent times received increasing attention as DSM programs (Gyamfi et al., 2018). In fact, any program intended to sway the energy use of a consumer can be classified as a DSM program. Several studies have explored and assessed the potential benefits of DR, most of which focused on the impact of price signals, price induced behavior change and smart meters (Campillo, Dahlquist, Wallin, & Vassileva, 2016). In such approaches, DR is designed to motivate or persuade energy consumers to make short-term cuts in their energy demand in response to price, financial incentive and hourly reliability signal from the electricity market or a trigger actuated by the electricity network operator when system reliability is threatened (Haghifam, Dadashi, Zare, & Seyedi, 2020; Shen, Ni, Ghatikar, & Price, 2012; Vivian, Chiodarelli, Emmi, & Zarrella, 2020; Wohlfarth, Worrell, & Eichhammer, 2020; Xiang, Cai, Gu, & Shen, 2020; Yahia & Pradhan, 2020). Vanthournout, Dupont, Foubert, Stuckens, and Claessens, (2015)) examined the performance of an experimental demand response based on day-ahead dynamic pricing of 58 households in Belgium from September 2013 to July 2014 using smart appliances such as domestic hot water buffers, washing machines, dishwashers and tumble dryers. The results indicate a significant shift of controllable share of the electricity consumption to low price periods. Torriti (2012) assessed the impact of time-of-use (TOU) tariff on electricity demand and load shifting at the sub-station level in the Province of Trento in Northern Italy. Meter reading data was collected for flat rate tariff for the period 1st July 2009 to 30th June 2010 and for TOU tariff from 1st July 2010 to 30th June 2011. Comparing the TOU to flat rate, the results indicate relatively higher average consumer electricity consumption of 13.69% but with reduced electricity spending of 2.21% while morning peak reduced through shifting. Bartusch, Wallin, Odlare, Vassileva, and Wester, (2011)) conducted an experimental study in Swedish households using semi-structured interviews to assess consumers' perception and experience with TOU tariff. The findings show 11.1-14.2% total electricity consumption reduction in 2005-2006 and shifting of loads to off-peak periods. Carroll, Lyons, and Denny, (2014)) analyzed data collected through randomized controlled smart metering trial in Ireland to understand the impact of smart meter use and TOU tariff in demand reduction. The study found 1.8% demand reduction as a result of smart metering program participation with TOU tariffs. Others have tested alternative means of administering feedback to consumers. Srivastava, Van Passel, and Laes, (2019)) used a quantile regression model based on survey data collected from 155 Belgian households to examine the influence of consumers' behavior and perception of smart appliances on demand flexibility. The results indicate 44.2% variance in demand flexibility due to consumers' behavior. Indeed, consumer behavior changes as a result of awareness creation. Adequate information on the benefits of smart appliances has the tendency to influence their energy use. It has been shown that depending on the building type and socio-economic characteristics of households, as much as 20% of total energy demand can effectively be managed by consumers if they become sensitized of their energy use (Fulhu, Mohamed, & Krumdieck, 2019). Ueno, Inada, Saeki, and Tsuji, (2006)) installed an on-line interactive system in 10 houses in Osaka, Japan to raise the energy-saving consciousness of household members through the provision of their energy consumption information. Results indicate that 18% reduction of their energy consumption was realized.

In recent years, the concept of voluntary demand response (VDR) is gradually becoming pronounced. VDR essentially focuses on the conscious decision of consumers to collectively change their behavior patterns to influence change in the proportion of used energy. The influencing signal for participation is often motivated by shared community objectives that are not limited to price. The motivations might include energy security concerns, environmental considerations, avoidable future electricity price hikes, and electricity market vulnerabilities (Fulhu et al., 2019). VDR is particularly pragmatic in regions where the grid network and metering architecture does not support time-dependent rates for electricity use or where low-income households consuming less electricity can be unfairly disadvantaged during peak periods where prices are hiked (Fulhu et al., 2019; Gyamfi, 2010). Gyamfi and Krumdieck (2011) conducted a study in Christchurch, New Zealand using diversified demand modeling approach to assess the impact of voluntary load shedding of residential household demand in response to price, environment and security signals. The findings show a potential reduction of 10% in peak demand for the total VDR. Fulhu et al. (2019) modeled the impact of VDR in HOMER for Fenfushi Island, Maldives with the objective of maintaining electric power for essential energy services and displacing fossil fuel use for more renewables. The results indicate reasonable renewables addition when consumers adjust their energy use voluntarily. VDR allows shifting of loads by getting consumers to put off appliances and larger industrial machines at peak times and to run such machines at specific off-peak hours instead, thereby changing the load profile to match the generation supply. This is particularly important for renewables integration in that, net load changes rapidly and VDR allows demand to be met flexibly and quickly to avoid curtailment of solar and wind generation (Avila, Carvallo, Shaw, & Kammen, 2017).

The presented reviews reveal that price-based DR exists mostly in areas where the grid network and infrastructure are smart to support such programs. VDR is an alternative that has the potential to provide significant technical and economic benefits. Ghana is amongst the Economic Community of West African States (ECOWAS) that is at the forefront of enacting and enforcing DSM regulation for electrical appliances in Africa. The primary focus of most DSM policies in Ghana is initiating regulations on energy efficiency standards and labeling (S&L). So far, S&L regulations have been promulgated for air conditioners, lighting (CFL), refrigerators and freezers (Diawuo, Pina, Baptista, & Silva, 2018), but opportunities related to DR are seldom discussed. No extensive model-based assessment of the economic and environmental potential of DR exist for most African countries, to inform policy-makers on enacting regulations that can effectively exploit the currently untapped DR 'energy resource'. The absence of such policy and legislation in the region has largely been attributed to lack of data and understanding of household consumers' behavior in response to DR requests and signals. This paper attempts to fill that knowledge gap by generating and providing such data for Ghana. Within this context, the study focuses on three main objectives;

- estimate and characterize the hourly variation of residential electricity load, and subsequently categorize flexible loads for potential demand response action,
- assess the peak reduction potential, economic and emission savings of shedding and/or curtailing controllable loads through voluntary actions by consumers in response to signals about the security of power supply, electricity prices and CO_2 emission concerns,
- identify barriers, discuss policy implications and suggest recommendations to incentivize voluntary demand response implementation.

A bottom-up approach based on an end-use model called the method of diversified demand is used. The model is calibrated using the measured appliance energy use data and validated while scenarios are created, and sensitivity analysis conducted to examine possible uncertainties.

The study focuses on Ghana's residential sector for 2 main reasons: 1) there is lack of data and proper understanding of household consumers' behavior to aid development of appropriate demand response strategies and 2) it is the highest contributor to national peak demand, and has the fastest sectoral growth in electricity consumption (Sakah et al., 2019). Residential electricity demand in Ghana has witnessed a rapid increase over time. The annual sectoral share hovers around 39% with an average annual growth of 3.3% since 2000 (Diawuo et al., 2019). Deploying EE and VDR measures together in the residential sector can provide combined benefits. VDR implementation in Ghana could ensure the security of power supply through induced energy conservation that could subsequently eliminate the need for expansion of generating facilities, saving both capital and operational cost (Lynch, Nolan, Devine, & O'Malley, 2019; Thakur & Chakraborty, 2016).

The originality and the main scientific contributions of the paper are summarized as follows:

- This study combines both survey information and monitoring data of hourly consumption for a wide range of household appliances to generate and make available to the scientific community, hourly load variation factors and diversified household peak demand of household appliances and other household load data which rarely exist in Ghana. To the authors' knowledge, this is the first study to publish disaggregated hourly residential electricity use that is based on measured data for Ghana. The study additionally provides detailed information on end-users' responsiveness and economic viability which is crucial in assessing the cost-effectiveness of different DR programs.
- The approach used in modeling the appliance stock over time was modified in comparison with similar studies to include the evolutional dynamics of appliance penetration and saturation which adequately captures consumers' choice and preferences. This method gives good estimates of the evolutional behavior of domestic electrical appliances and its ownership, thus, providing a better understanding of the reality.
- The evidence for rebound effect is very weak in many developing countries. Though the development and implementation of DSM policies are still in the early stage for many developing countries, the impact of rebound effect are lacking and largely unexplored. The sensitivity analysis conducted in this study on rebound effect gives a suggestion of some margin of uncertainty around the future consumption if concerted efforts are not made to address consumer behavior in the use of energy services. Indeed, these uncertainties should provide the rationale for policy makers to enact policies to match up and realign possible inactions even if the concept might be overplayed.
- Often the potential assessment of DSM strategies and its opportunities in developing and less developed countries are seldom discussed because it is assumed that there is poor metering infrastructure, sporadic load data, low investment support, low income, etc. to support such initiatives and actions. This study has shown that there exist significant potential and benefits from demand response programs and therefore provides a learning curve and policy direction for Ghana and other African countries that are in the initial phase of developing DSM policies.

The remaining parts of the paper are structured as follows. Section 2 presents the survey design approach, data collection, appliance monitoring and methodological approach used in determining the impact of demand response. Section 3 introduces the results of the developed scenarios on peak demand and the impact of demand response on emissions, cost-benefit analysis, and policy implications. Section 4 concludes the paper with limitations and future works.

2. Data and methods

This section provides details of the data collection and DR modeling approach, as well as data assumptions and definitions of scenarios.

2.1. Data collection

The main source of information for the characterization of electricity use in Ghana was a household survey combined with metering of household appliance usage conducted in the period from February to July 2018. The questionnaires were performed by trained students and guided by researchers. More detailed information on this survey is presented in the next section.

2.1.1. Survey design

The survey method involved the deployment of a questionnaire with in-person interviews and key members of the randomly selected households across Ghana with a total sample of 80 households. A guided oral interview was administered in households where illiteracy was encountered. The respondents who provided responses to the questionnaires were assumed to be a representative of the household although the response to DR motivation factors is opinionated. The content of the survey principally concentrated on 2 broad thematic areas which included energy audit information and demand response motivation signals. The energy audit section included household characteristics, building features and electricity usage. The household characteristics consisted of the household size, the average age of household members, income levels, job status and educational level and floor size. The building features included the building type, number of rooms and floor size. The electricity usage included the type of appliances, power ratings, electricity use activity pattern and electricity bills. The DR motivation signal section included information related to appliance preferences for demand response action, type of demand response action and motivation factor (electricity price, energy security and environment) preferences.

The demographic and socioeconomic characteristics of the 80 sampled households are representative of the different types of Ghanaian households because it spread across the entire country and captures households with different electricity consumption patterns, income levels, building types, ethnocultural dynamics, etc. The questionnaires were distributed over the entire country based on population density with close to 40% administered in the northern belt and 60% in the southern belt. A statistical package for social science (SPSS) tool was used to conduct a simplified statistical analysis on the collected data. Some selected descriptive statistics indicating the mean, frequency, etc. on the data are presented in Table 1.

Fig. 1 presents a histogram of some selected household and building characteristics parametric output data. A quite significant number of respondents (94%) have a family size of between 2-6 persons. About

Table 1
Descriptive statistics for collected data.

Variable	Count (N)	Unit	Mean	Std. dev	Min.	Max	Mode
Electricity consumption	80	kWh/yr	2939	2505	398	12890	
Income level	80	US$/month	927	696	124	3654	567
Floor size	80	sq. meters	123	86	31	428	96
Household size	80	persons	4.2	1.4	1.0	7.0	4.0
Averaged age of household member	80	years	49	11	29	76	56

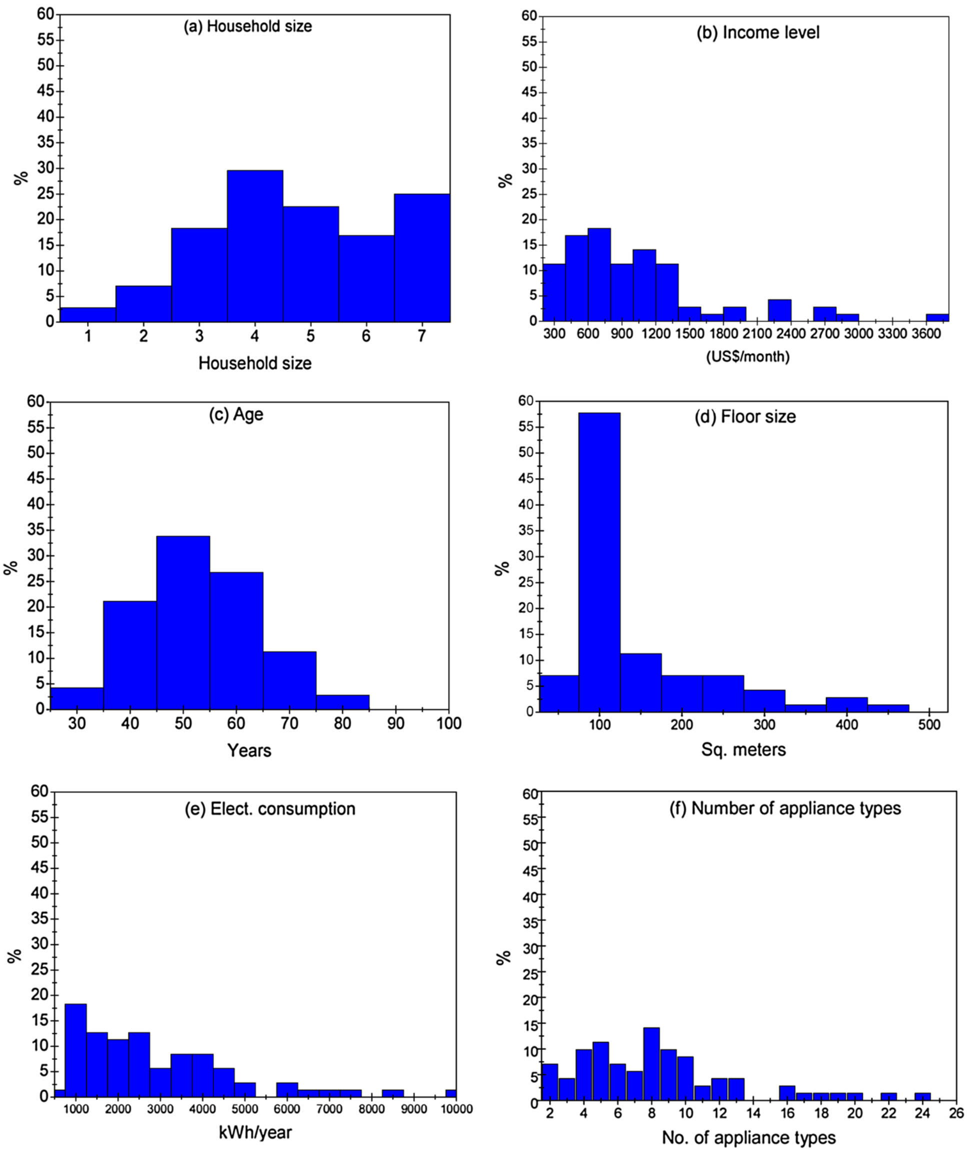

Fig. 1. Percentage share (a) household size (b) income (c) average age of household members (d) floor area (e) electricity consumption and (f) number of appliance types (N = 80).

75% of the respondents earn a monthly income of between 500-1500 US$. The majority of households representing 93% have a varying average age of 40-70 years. Respondents representing 94% live in a house having an average floor area of 50-300 m^2. Annual electricity consumption based on aggregate monthly electricity bills indicates that most of the households (77%) consume electricity between 1000-4000 kWh/year and a significant share of the households (80%) possess between 2 and11 different types of appliances.

2.1.2. End-use monitoring and load profiles

Appliance energy use monitoring and energy meter reading was conducted in all the 80 sampled households within the survey period to secure power consumption data. Additionally, household activity patterns such as cooking, eating, washing, etc. times were observed to appreciate the reasons for appliance energy use variation patterns. The power consumption data was gathered for 12 commonly used appliances in the household and lighting. The selected appliances are considered to the most owned and used in many Ghanaian homes as recorded in the standard of living survey reports conducted by the Ghana Statistical Service (Ghana Statistical Service (GSS) (1995), 2000, 2008, 2014). The 12 appliances include a personal computer, electric iron, television, satellite receiver, electric kettle, washing machine, electric boiler, microwave oven, refrigerator, rice cooker, electric fan and air conditioner. Different measurement devices and power analyzer data loggers with a time resolution of 30 minutes were used in the representative households to monitor appliance and lighting energy use over 24 hours each day for the entire monitoring campaign period. To ensure an accurate reading, the measuring devices were initially calibrated for comparable readings beforehand. A serial wattmeter was used to measure the power consumption of some appliances (e.g. refrigerator, television, etc.). The device was plugged directly into wall sockets and connected in series with the appliance through its trailing socket. Other appliances that are hardwired to circuit breakers such as air conditioners and washing machines were measured directly from the distribution switchboard panel of the house. The energy detective (TED)[1] device with a current rating of up to 200 Ampere was installed in the circuit breaker to monitor energy use. Lamp meters were used to measure the energy use of all lamps (fluorescent, CFL, LED, etc.) that drew constant power. The billing meters were continuously monitored

[1] TED-The Energy Detective (brand)

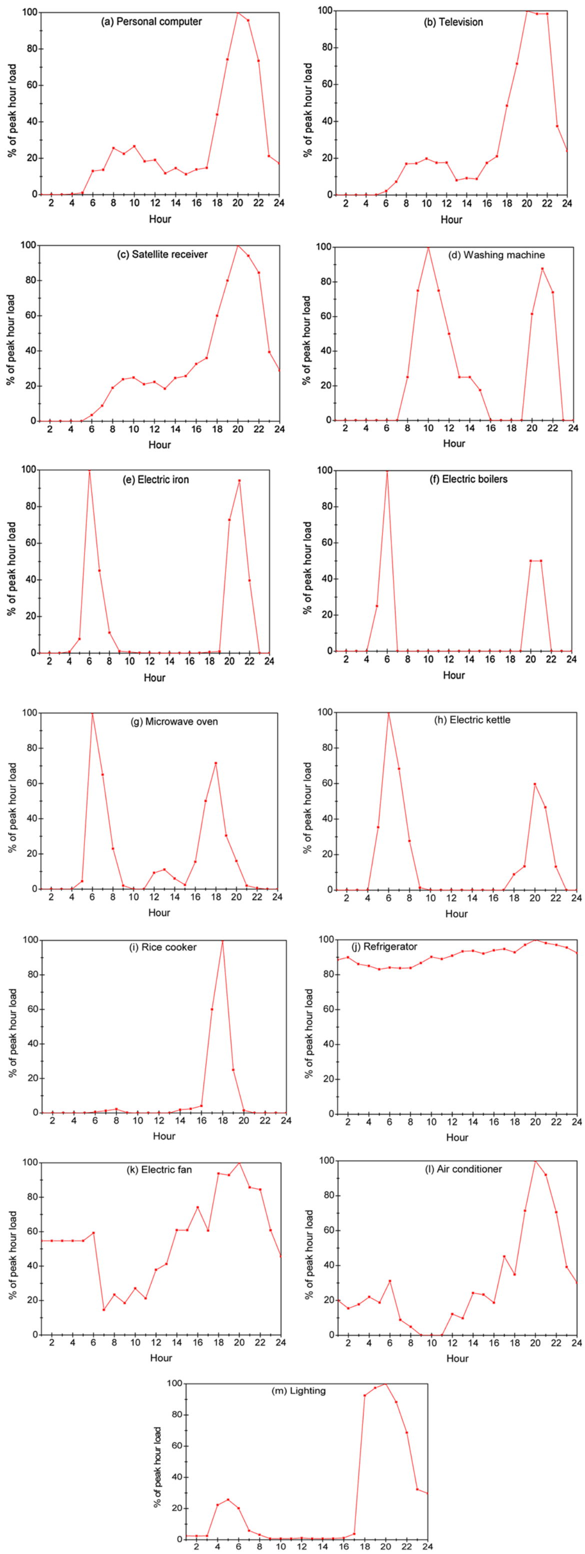

Fig. 2. Hourly variation factors for monitored appliances (a-l) and lighting (m).

to investigate and account for other possible loads not considered. The recorded data were then averaged for an hourly period to acquire the daily load profile for a typical day. The hourly load variation factors for each appliance was estimated by dividing the hourly average load by the peak load. The hourly variation factors show the activity periods and the behavior characteristics in the usage of an appliance. This often depends on the unique individualities and lifestyle of energy users in a specific location. The lifestyle is mostly influenced by several factors including; the number of household occupants, income levels, type of housing, education level, employment status, age, climate conditions, etc. (Gyamfi & Krumdieck, 2011; Hamidi, Li, & Robinson, 2009). Fig. 2 shows the hourly load variation factors for all appliances and lighting from the monitoring campaign.

2.1.3. Voluntary demand response (response from respondents/consumers)

Respondents were asked for their willingness to participate in demand response action which would shift or/and curtail their load during peak periods under a certain motivating signal (electricity price, energy security and environment). Additionally, respondents were asked to indicate which appliances they were willing for it to be part of the DR program and which motivating signal will influence their decision to engage in such a program. The motivating signals used in this study is premised on some historical factors which have the tendency to influence elasticity in electricity demand. Energy security is a major concern as Ghana has a perennial record of load shedding due to supply shortages. As a result of power shortage, a 2013 projection by the Energy Commission of Ghana highlighted an unmet demand of 240-330 MW which influenced a stunt in economic out-turn with a drop in real GDP from 8.8% in 2012 to 7.1% in 2013 (Energy Commission of Ghana, 2014). In relation to electricity price, the Grid operators, GridCo, indicated that in December 2015, consumers responded to a 59% price increment in electricity tariff with changes in their consumption patterns which reduced demanded power significantly (GRIDCo, 2017; Sakah, De la Rue du Can, Diawuo, Delight, & Kuhn, 2019). The environmental factor is borne out of the global direction toward energy decarbonization and climate change considerations. To indicate willingness to partake in DR for each appliance, a value of either 1 or 0 is assigned where 1 indicates willingness and 0 represents unwillingness. To determine the percentage of participation of DR for each appliance with household ownership, the willingness value is summed for each appliance and divided by the total sum of both willingness and unwillingness to participation and multiplied by 100. The participation percentage for each appliance is shown in Table 2. At this stage, a response to a possible voluntary demand response participation for all appliances is presented though not all are practically controllable. Television, electric fan, electric iron and refrigerator showed the highest participation willingness while electric kettle and rice cooker were the lowest.

To determine the influence and percentage weight score of each motivating factor, respondents had the liberty to tick more than one factor for each appliance which could influence their participation. The factors were assigned the same weight of 1. The number of ticks for each factor is then summed across all the appliances under consideration and divided by the total possible score and multiplied by 100. Table 3 shows the weight score of the motivation factors and the

Table 2
Willingness of DR participation.

Appliance	DR participation (%)
Personal computer	20%
Television	68%
Satellite	33%
Washing machine	23%
Electric iron	52%
Electric boiler	32%
Microwave oven	20%
Electric kettle	18%
Rice cooker	18%
Refrigerator	48%
Electric fan	58%
Air conditioner	25%
Lighting	–

Note: Lighting was not included because of its necessity for vision.

Table 3
Weight score of motivation factors.

Appliances	Motivation factors			Total
	Prices	Security	Environment	
Personal computer	5	7	0	12
Television	23	17	1	41
Satellite	14	6	0	20
Washing machine	8	6	0	14
Electric iron	19	12	0	31
Electric boiler	0	1	0	1
Microwave oven	9	3	0	12
Kettle	7	4	0	11
Rice cooker	5	6	0	11
Refrigerator	11	18	0	29
Electric fan	14	21	0	35
Air conditioner	9	5	1	15
Lighting	–	–	–	–
Maximum possible for each	124	106	2	232
Percentage weight score (%)	**53%**	**46%**	**1%**	

Note: Lighting was not included because of its necessity for vision.

responses indicate a high percentage weight score for electricity prices signal followed by energy security with the environment being the lowest.

2.2. Methodology: Demand response model

A bottom-up approach based on an end-use model known as the method of diversified demand (Gyamfi & Krumdieck, 2011; Turan, 2014) is used with energy audit data to estimate the peak load reduction potential from the DR programs. This method is effective and delivers high accuracy in modeling residential demand response because it offers a component-by-component analysis of the electrical load (Gyamfi & Krumdieck, 2012). The method relies on appliance usage behavior and the fact that households might not be using all the electrical appliances that constitute the connected load of the house at the same time and/or to their full capacity (Gyamfi & Krumdieck, 2011). It accounts for the diversity between similar loads and the noncoincidence of the peaks of different types of loads. The method thus enables an estimation of aggregate appliance-based load curve for residential consumers from most predictable loads. To develop and determine the residential end-users load curve and demand response impact, model input information such as the diversified household peak demand, appliance ownership, number of households, hourly load variation factors, degree of appliance control and electricity consumer willingness for demand response participation is required. Fig. 3 shows the flowchart for load curve estimation and DR model.

The appliance ownership is the average number of an appliance unit in the household. A logistic function as presented in Eqs. (1 and 2) is used to model the appliance ownership as a sigmoid function of time as it ably captures consumer preference which is influenced by appliance saturation and penetration (Diawuo et al., 2018). The model accuracy is ensured using the statistical metric, Root Mean Square Error (RSME) which predicts the error between the actual and the modeled data (Diawuo et al., 2019; McNeil & Letschert, 2010).

$$\gamma_t^a = \frac{S^a}{1 + e^{\log_e(S^a/\beta^a - 1) - bt}}; \quad S = a \times p;\ where \begin{cases} a \geq 1 \\ p \leq 1 \end{cases} \quad \beta = a \times p;\ where \begin{cases} a = 1 \\ p \leq 1 \end{cases} \tag{1}$$

$$b = \frac{\log_e(S^a/\beta^a - 1)}{\vartheta(t)} \tag{2}$$

where γ_t^a is the ownership of appliance, a at time t (unit/HH); S^a is the theoretical future (maximum) ownership of appliance, a at t = 60; β^a is the initial ownership of appliance, a at t = 0; b is the scale parameter; t is the time in years (e.g. 0 for 1990); ϑ(t) is the abscissa inflection point; ρ is the appliance penetration and α is the saturation level.

The appliance stock is the total number of appliances often used in the households and it is estimated as the product of the appliance ownership and the total number of households in a specified year as presented in Eq. (3). The households number for a specific year is calculated by dividing the total population by the average household size of that year.

$$Stock^a = HH \times \gamma^a \tag{3}$$

where $Stock^a$ is the number of appliance, a units; γ_t^a is the ownership of appliance, a at time t (unit/HH) and HH is the total number of households.

To calculate the average maximum diversified demand of an appliance type, the appliance stock is multiplied by the diversified household peak demand as shown in Eq. (4). The diversified household peak demand (DHPD), measured in kW is obtained by dividing the coincident peak demand of each appliance by the number of households (Konstantelos, Sun, & Strbac, 2014).

$$MDD_{av}^a = DHPD^a \times Stock^a \tag{4}$$

where MDD_{av}^a is the average maximum diversified demand of appliance, a and $DHPD^a$ is the diversified household peak demand for appliance, a.

The hourly maximum diversified demand for a type of an appliance is given by Eq. (5) and it is expressed as the product of the average maximum diversified demand and the hourly variation factors of the appliance used over the course of the day.

$$MDD_t^a = MDD_{av}^a \times \lambda_t^a \tag{5}$$

where MDD_t^a is the maximum diversified demand of appliance a, at any time, t of the day; λ_t^a is the hourly variation factors of appliance, a.

The hourly maximum demand for the total combined appliances used in all the households at any hour of the day is presented in Eq. (6)

$$MRL_t = \sum_{a=1,\dots}^{n} MDD_t^a = \sum_{a=1,\dots}^{n} \gamma^a \times HH \times DHPD^a \times \lambda_t^a \tag{6}$$

where MRL_t is the total combined maximum demand of all appliances and lighting at any hour of the day.

2.2.1. Demand response behavior

When a proportion of households show willingness to participate in DR program before the action is implemented (pre-event stage), the combined hourly maximum demand is as expressed in Eq. (7).

$$E_t^{BDR} = \sum_{a=1,\dots}^{n} MDD_t^a \times DRP^a + \sum_{a=1,\dots}^{n} MDD_t^a \times (1 - DRP^a) \tag{7}$$

where E_t^{BDR} is the maximum demand of consumers at any hour of the day before DR action and DRP^a – demand response participation is the percentage of households participating in DR for a specific type of appliance, a.

The combined hourly maximum demand after a specific demand response action (event stage) is implemented is given by Eq. (8).

$$E_t^{ADR} = \sum_{a=1,\dots}^{n} MDD_t^a \times DRP^a \times DRC_t^a + \sum_{a=1,\dots}^{n} MDD_t^a \times (1 - DRP^a) \tag{8}$$

where E_t^{ADR} is maximum demand of consumers at any hour of the day after DR action implementation and DRC_t^a is the degree of control for a specific type of controllable appliance, a at specific hour of the day.

The theoretical demand reduction or savings as a result of DR action at peak hours in the day is given by Eq. (9) and it is expressed as the difference between the maximum demand before and after DR action implementation.

$$\Delta E_t^{DRS} = E_t^{BDR} - E_t^{ADR} \tag{9}$$

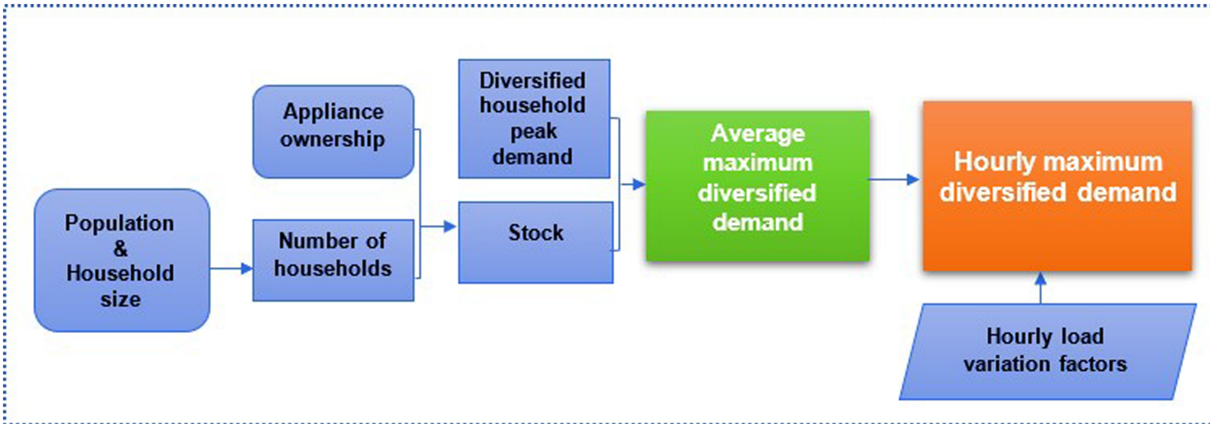

Fig. 3. Flowchart of the modeling approach.

where ΔE_t^{DRS} is the theoretical peak demand reduction.

Percentage of demand reduction at peak hours is as presented in Eq. (10)

$$\%PDR = \frac{\Delta E_t^{DRS}}{E_t^{BDR}} \times 100 \tag{10}$$

2.2.2. Emission savings

The CO_2 emission saved through the implementation of DR action as shown in Eq. (11) is a function of the peak demand reduction and the electricity emission factor.

$$ES_t = \Delta E_t^{DRS} \times EEF_t \tag{11}$$

where ES_t is the emission savings and EEF_t stands for the electricity emission factor ($kgCO_2/kWh$) which varies over time based on the primary energy sources mix and the power generation.

2.2.3. Demand response cost

Net present value (NPV) is used to assess the economic viability and cost-effectiveness of implementing DR action programs in households, quantifying the value to be created for the utility providers. The NPV is the sum of all the cash flows discounted to the present using the time value of money (Crundwell, 2008). If the NPV is greater than zero, it is anticipated that value will be created for the utility providers. If it is less than zero, it shows the economic non-viability of the investment. The NPV is formulated (Crundwell, 2008) as shown in Eq. (12).

$$NPV = \sum_{i=0}^{n} \frac{CF_i}{(1 + k_i)^i} \tag{12}$$

where CF_i is the cash flow at year i, n is the life or horizon of the investment of the DR program and k is the discount rate.

2.3. DR load classification

Residential appliances have different operating characteristics and working cycles (Staats, de Boer-Meulman, & van Sark, 2017). The flexibility in the usage patterns of some of the appliances can somehow be managed to reduce their consumption during a certain time period. Demand control is possible since some consumers' need for certain energy services might not be coincident with consumption of electricity (Soares, Gomes, & Antunes, 2014). In some circumstances, electricity consumption can be altered with slight changes in the level of energy service at some short periods with insignificant changes in energy service quality. On the contrary, some appliances might be difficult to control, not due to technical or technological constraints but because of the high tendency to disrupt the quality of energy service and comfort of energy users. Residential loads have been classified into 3 broad categories based on the type or degree of control (Soares et al., 2014):

- Non-controllable loads: are the type of loads that are likely to cause discomfort or disruption of activities to electricity consumers. Examples of such loads or services include; lighting, cooking and entertainment appliances, etc.
- Thermostatic controlled/interruptible loads: are types of loads whose operations can be interrupted with a reset or adjustment of the thermostat without generating discomfort or altering the quality of energy service. Example of such loads or services include; refrigeration, air conditioning and water heating appliances)
- Shiftable loads: are the type of loads whose working operation can be postponed or rescheduled to another time without discomforting the consumer or decreasing energy service quality. Examples of such loads or services include; water heating, ironing, dishwashers, washing machines, clothes dryers, etc.

In this study, the monitored appliances have been classified as shown in Table 4 and only thermostatic controlled and shiftable loads were used in the DR control analysis even though in the DR motivation survey responses, respondents indicated readiness and willingness to voluntarily allow all appliances to partake in the DR programs under certain signal sensitivities.

2.4. Scenarios and data assumptions

2.4.1. Scenarios definition

The scenarios developed were based on the demand response control strategy and the fraction of representative households that show the willingness to participate in the DR program for the determined controllable appliances. The uncertainties surrounding consumer behavior and the level of participation in the implementation of DR programs form the basis for the selection of these scenarios. Peak demand reduction through demand response action can only be successful if consumer behavior and their willingness to partake in the program becomes central. Without the support and co-operation of the consumers, DR implementation can be redundant and unproductive (Gyamfi & Krumdieck, 2012; Parrish, Heptonstall, Gross, & Sovacool, 2020). The DR control strategy has 3 levels; demand shifting, demand curtailing through thermostatic control/interruption and the combination of the two (load shifting plus load curtailing) at end-users coincident demand during peak periods. The DR participation has 2 levels; Base which is the baseline percentage of participation by representative respondents and High which represents a 50% increment in the Base scenario. Six different scenario combinations (S1-S6) were formed as shown in Fig. 4 and its impact analyzed.

Table 4
DR load categorization.

Non-controllable load	Thermostatic controlled/interruptible load	Shiftable load
Personal computer, microwave oven, television, electric kettle, satellite receiver, rice cooker and lighting.	Electric boiler, refrigerator, electric fan and air conditioner.	Washing machine and electric iron.

2.4.2. Data assumptions

This subsection presents the assumptions on population, household size, appliance ownership, diversified household peak demand, emission factors, DR costs and degree of load control used in the study.

2.4.2.1. Population and household size. Using the single compound amount method, dataset for population and household size were estimated for the period between 2018 and 2050 based on data reports sourced from the Statistical Service of Ghana (GSS) (Ghana Statistical Service (GSS) (1995), 2000, 2008, 2014), World Bank (2017) and United Nations (2015). The baselines used for the population, household size and the number of households are presented in Table 5. The population and household size for Ghana between 2018 and 2050 are estimated to grow at an average annual rate (AAGR) of 1.74%, and -0.31% respectively (Ghana Statistical Service (GSS) (1995), 2000, 2008, 2014); United Nations, 2015; World Bank, 2017).

2.4.2.2. Appliance ownership. The appliance ownership is influenced by many factors, including; income, urbanization, electrification rate, lifestyle, climate, etc.(Diawuo et al., 2018, 2019; McNeil & Letschert, 2010; McNeil, Letschert, de la Rue du Can, & Ke, 2013). To model the appliance ownership evolution, the initial (β^a) and future (S^a) ownership parameters data are key and these data are sourced from Diawuo et al. (2019). The actual data used for the statistical comparison is sourced from the GSS through its living standard survey reports (GLSS) (Ghana Statistical Service (GSS), 1995, 2000, 2008, 2014). The appliance ownership evolution for considered appliances until 2050 is shown in Fig. 5. Root Mean Square Error (RMSE) used to predict and compare the errors between the modeled and actual data indicates values varying between 0.002 and 2.468. The low values indicate a better fit.

2.4.2.3. Diversified household peak demand (DHPD). The DHPD data is obtained from the metering records conducted in the representative households and it is presented in Table 6. In respect of the time horizons analyzed, the DHPD for all appliances is assumed to be the same as the measurement year 2018, although possible future policy initiatives and consumer lifestyle situations like energy efficiency and conservation improvements or the concept of rebound effect could have an appreciable impact.

Table 5
Baseline assumptions for household indicators (Ghana Statistical Service (GSS), 1995, 2000, 2008, 2014; United Nations, 2015; World Bank, 2017).

Indicator	2018	2030	2050
Population (inhabitants)	28,862,700	35,485,869	50,071,000
Household size (number of people)	3.94	3.80	3.57
Number of households	7,327,428	9,347,360	14,025,490

Note: AAGR for number of households between 2018-2050 is 2.05%.

2.4.2.4. Load profiles. In analyzing the impact of DR, the hourly variation factors of appliances were developed for both groups of representative households who indicated their willingness to participate in the DR program and those who showed an unwillingness to participate using the measured data. The average load factors between the 2 groups showed an absolute relative difference of about 2%.

2.4.2.5. Emission factors. The emission factor is assumed based on the fuel mix diversification in electricity generation. The choice of a power plant in electricity generation varies in time depending on the availability of power plant, demand (base, intermediate and peak), cost of fuel and generation, etc. The medium-long term primary energy sources for the power plants are hinged on hydro, non-conventional renewables (solar) and ideally natural gas and/or crude oil which feature in generation expansion projects as forecasted by the utility providers (GRIDCo, 2018). Table 7 presents the emission factors used in estimating the CO_2 saving relying on the reduced peak demand under the DR programs.

2.4.2.6. DR costs and discount rate. The implementation and operation of DR programs impose costs on both household DR participants and utility providers. The participants cost spread across initial and event-specific costs related to smart thermostats, energy management systems, comfort/inconvenience costs, rescheduling costs, etc. (Aghaei & Alizadeh, 2013; Bradley, Leach, & Torriti, 2011). The utility providers cost in relation to the initial and ongoing program costs include metering and communication infrastructure cost; software and billing system upgrade costs; consumer education and administration

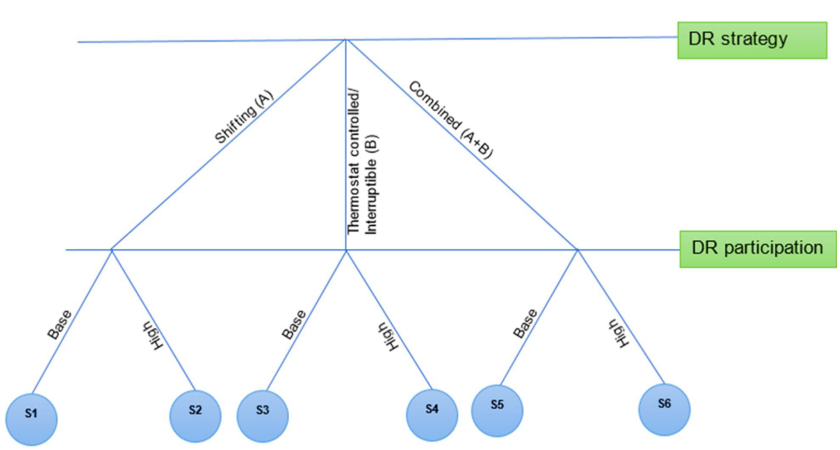

Fig. 4. Definition of DR scenarios.

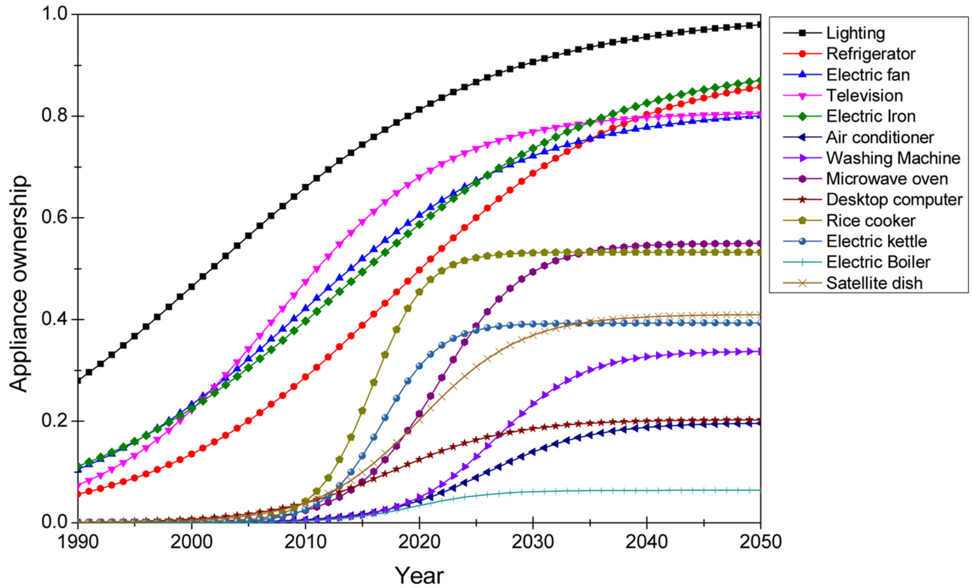

Fig. 5. Modeled appliance ownership evolution.

costs; incentives and payments to participating consumers, etc. (Bradley et al., 2011). This study assumes that participating consumers are offered incentives in a form of free communicating thermostats through which the utility provider controls devices remotely while on load shifting, human intelligence is relied upon through education campaigns and incentive support. Costs are assigned to utility providers, but a zero cost is assumed for participating consumers. The benefits in implementing DR programs are numerous, both the participants and utility providers are beneficiaries. Some of the avoided costs include; avoided energy costs, avoided capacity costs, avoided transmission and distribution (T&D) costs, avoided environmental compliance costs, avoided environmental externalities, avoided ancillary service costs, etc. (Woolf, Malone, Schwartz, & Shenot, 2013). The costs used in the economic analysis for the scenarios created are as shown in Table 8. The cost component can vary significantly from one utility provider to another because of differences in cost drivers. A discount rate of 7.5% is assumed (CBONDS, 2018) in line with the recent bond issued by Ghana and used for the economic evaluation.

2.4.2.7. Degree of DR load control. Assumptions are made to control the load classified in Section 2.3 in respect to their degree of control and likely impact on the daily average load curve: thermostatic load reset will have a 25% decrease in appliance electricity consumption during peak hours (Conchado, Linares, Lago, & Santamaría, 2016; Malik, Haghdadi, MacGill, & Ravishankar, 2019; Soares et al., 2014) while for the load shifting, the total energy demand remains unchanged, instead a 100% of the total load of each day-type is seen movable in time to off-peak hours (Conchado et al., 2016). The possibility of the “snapback” or “payback” effect in the thermostatic loads is not accounted for because an increase in the average temperature threshold of 1 °C over the DR event period is considered but tested as a sensitivity analysis.

Table 6
Diversified household peak demand (DHPD) of appliance.

Appliance	DHPD (kW)
Personal computer	0.030
Television	0.049
Satellite	0.004
Washing machine	0.070
Electric iron	0.012
Electric boiler	0.040
Microwave oven	0.047
Kettle	0.010
Rice cooker	0.020
Refrigerator	0.087
Electric fan	0.060
Air conditioner	0.120
Lighting	0.010

3. Results and discussions

3.1. Model validation and accuracy

To evaluate the model robustness, the estimated hourly maximum demand curve of the households is compared to a typical national aggregated multi-sectoral daily load profile measured by the grid operator (GridCo) since disaggregated profile specific to the residential sector is non-existent. The shape of the modeled demand curve compares very well with the grid operator’s load profile as shown in Fig. 6 and shows an RMSE of 0.288, indicating a good fit. The critical peak hours occur between 6-10 pm. The magnitude of the average daily demand of the model represents a weight share of 34% of that of the grid operator’s load profile. The 34% is relatively close to the recorded 39% share of the residential sector in annual sectoral electricity consumption (Diawuo et al., 2019).

3.2. Load categorization

The share of the modeled residential demand to the national system load peak demand is about 49% reflecting a significant contribution to peak demand. About 90% of the average critical peak hour demand is consumed by 4 appliances and lighting loads: refrigerator (32%), electric fan (27%), television (22%), air conditioner (3%) and lighting (6%) as shown in Fig. 7(a).The modeled hourly maximum demand is disaggregated and categorized into the defined demand response load

Table 7
CO_2 emission factors (estimates based on (Diawuo & Kaminski, 2017)).

Year	2018	2030	2050
Emission factor ($kgCO_2/kWh$)	0.236	0.238	0.244

Table 8
DR costs components (adapted sources (Dranka & Ferreira, 2019; Gyamfi & Krumdieck, 2012; Mims, Eckman, & Schwartz, 2018; Piette, Schetrit, Kiliccote, Cheung, & Li, 2015; Ruble & Karaki, 2013)).

Implementation/avoided costs	Amount and unit	Shifting (A)	Thermostatic/ interruptible (B)	Combined (A + B)
Implementation cost				
Metering/communication & DR control devices	123.00 US$/consumer	–	X	X
Education campaign	2.46 US$/consumer	X	–	X
Administrative	1.23 US$/consumer	X	–	–
Avoided cost at peak				
Capacity cost	71.50 US$/kW	X	X	X
T&D cost	80.00 US$/kW	X	X	X
Emission cost	10.00 US$/t$CO_2$	X	X	X

Note: The time value of money is accounted for the costs over time based on the discount rate. The education campaign and administrative costs are assumed to be 2% and 1% of the metering/communication & DR control device cost. A tick of “X” indicates cost is included while “– “shows non-inclusive of cost component.

control as represented in Fig. 7(b). The weighted share of the thermostatic loads to the average daily demand is around 81% while shiftable and uncontrollable loads represent 2% and 17% respectively. On average, the contribution of thermostatic loads to critical peak demand between 6-10 pm is about 59% while shiftable and uncontrollable loads constitute 4% and 37% respectively. This shows that the contribution of controllable loads to households' peak demand is about 63% which is quite significant and thereby creates a viable opportunity for demand response implementation.

3.3. Scenario analysis

Fig. 8 and Fig. 9 show the daily demand curves for all scenarios before the DR event and the comparative difference after DR event respectively while Table 9 presents the average daily peak demand reduction. For brevity,the results are presented at periodic time intervals 2018, 2030 and 2050. The household demand curves show a small morning peak around 6 am when most household members are awake and involved in different preparatory activities before leaving for their workplaces while the critical peak occurs between 6-10 pm when most people are back home and engaging in different activities which require energy end-use services such as lighting, cooking, entertainment, laundry, air conditioning, etc.

In 2018, the maximum daily peak demand for all scenarios before the DR event was 938 MW and occurred around 8 pm. During the event period, the daily critical peak demand showed an average reduction varying between 12-109 MW (percentage reduction of 2-13%). The scenario with the highest peak reduction was S6 (Combined + High) followed by S4 (Thermostatic + High), S5 (Combined + Base), S3 (Thermostatic + Base), S2 (Shiftable + High) and S1 (Shiftable + Base) respectively. The contribution of appliances to the highest peak demand reduction from the S6 scenario indicate a weight share of washing machine (2%), electric iron (14%), electric boiler (nearly 0%), refrigerator (47%), electric fan (35%) and air conditioner (2%). The appliances with the lowest share have relatively lower household ownership and use. The scenario with the lowest peak demand reduction, S1 (Shiftable + Base) has washing machine and electric iron contributing 14% and 86% respectively. The shiftable loads which are user-defined showed their use moving from the peak period to the off-peak periods. The use of washing machines based on the model moved from the evening critical peak hours, 8-10 pm to 5-7 am while the electric iron moved from 8-10 pm to 1-3 pm.

By 2030, the maximum daily peak demand increased to 1807 MW, almost doubling that of 2018. This reflects the increasing appliance stock and its use during peak periods. The scenarios showed a critical peak demand reduction ranging from 33-220 MW (percentage reduction of 2-14%). Scenario 6 had the highest peak demand reduction while scenario 1 had the lowest. The weight share of appliances to the contribution of reduced peak demand for all scenarios varied; washing machine (0-47%), electric iron (0-53%), electric boiler (nearly 0%),

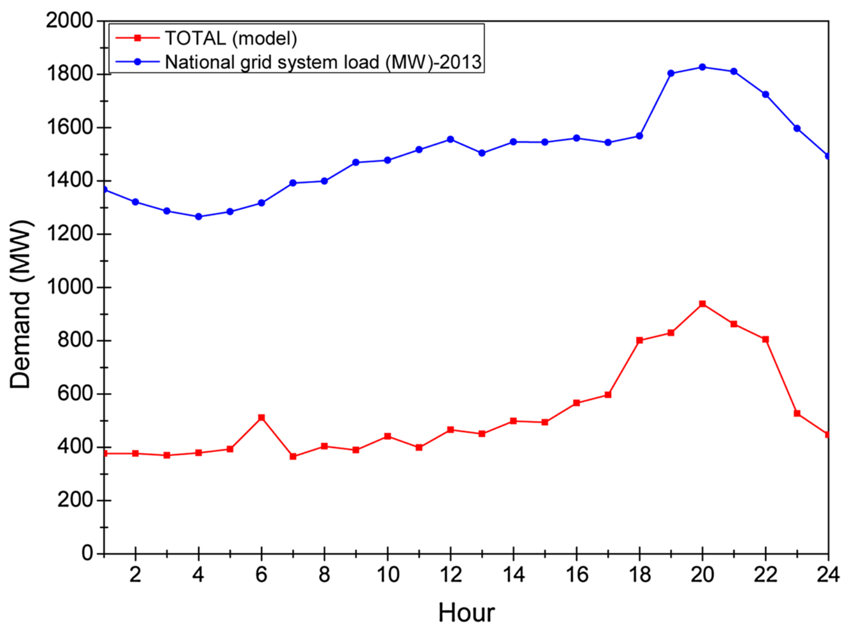

Fig. 6. Comparison of modeled and measured (national grid system load) daily demand.

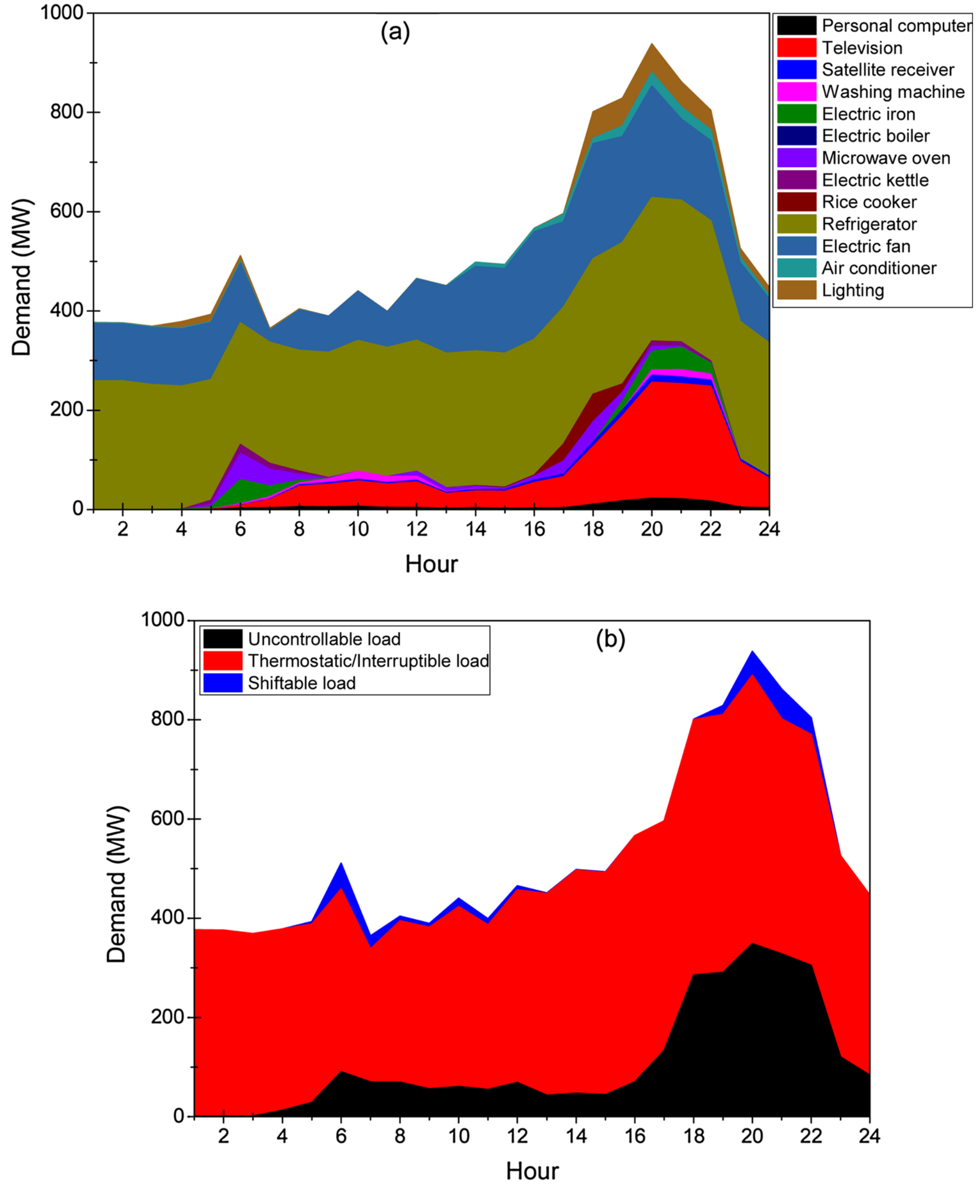

Fig. 7. (a) Average daily load curve by end-uses and (b) demand response load classification.

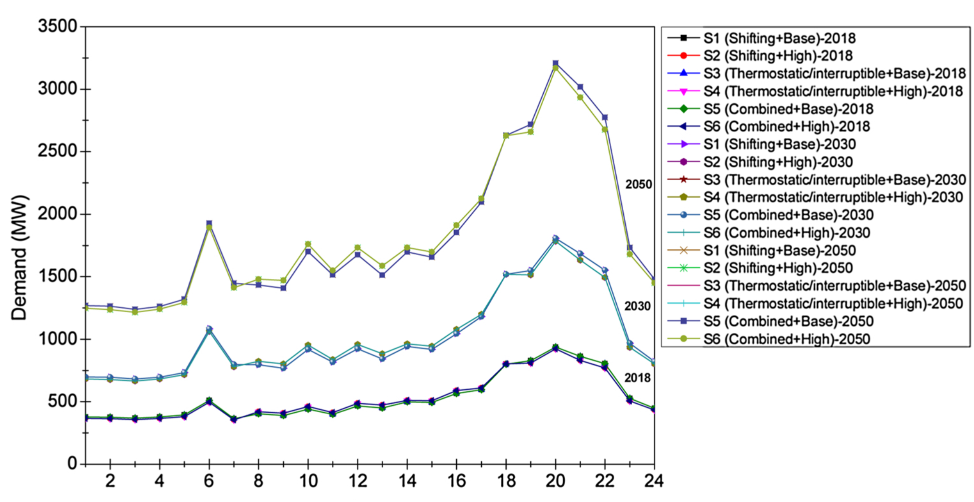

Fig. 8. Estimated load curves on a typical day for baseline scenarios before DR for 2018, 2030, 2050.

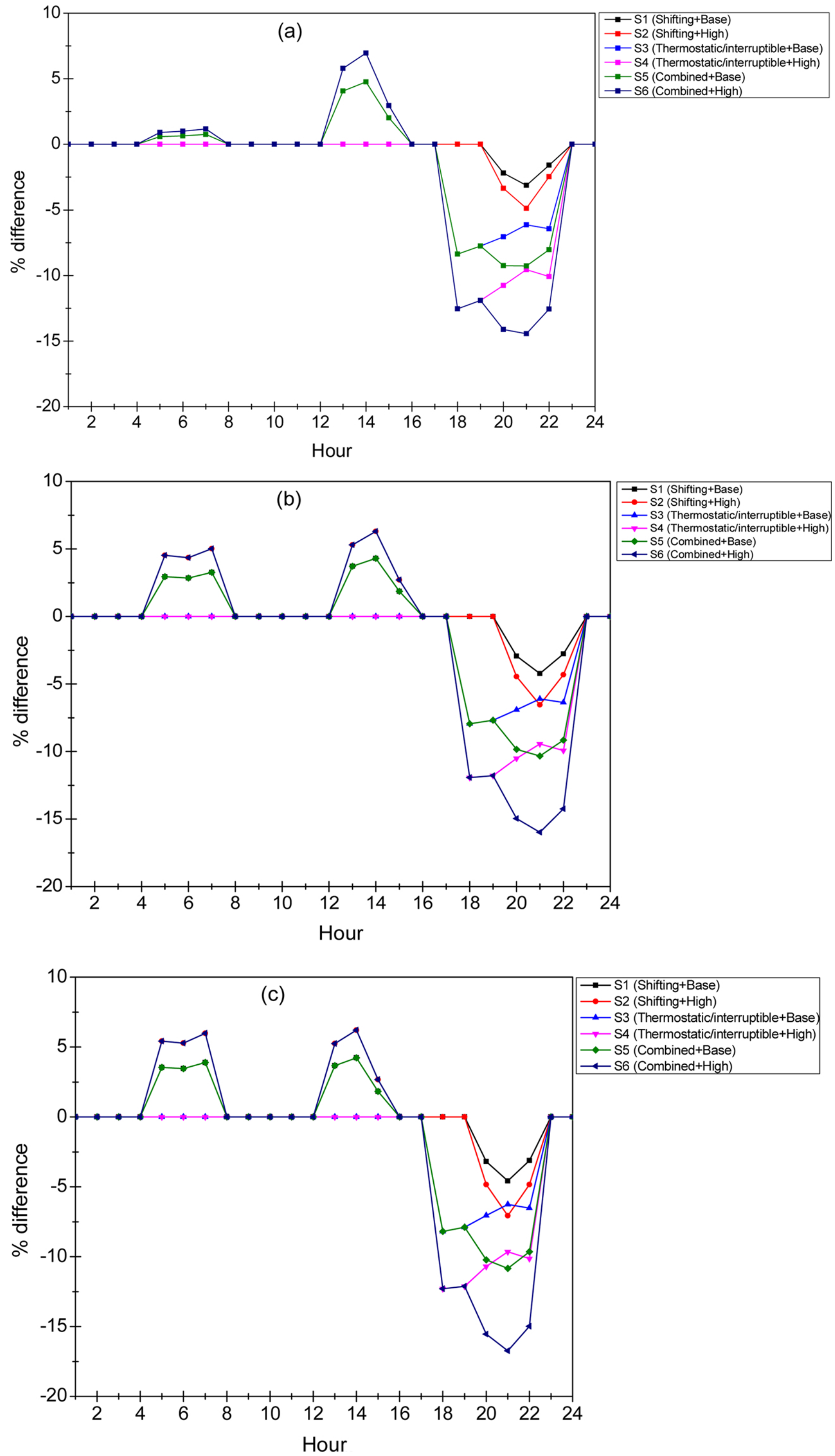

Fig. 9. Percentage comparison before and after DR for (a) 2018, (b) 2030 and (c) 2050.

Table 9
Average daily peak demand reduction (MW).

Scenarios	2018	2030	2050
S1 (Shifting + Base)	12	33	65
S2 (Shifting + High)	18	50	98
S3 (Thermostatic/interruptible + Base)	60	113	205
S4 (Thermostatic/interruptible + High)	91	170	308
S5 (Combined + Base)	73	147	271
S6 (Combined + High)	109	220	406

refrigerator (0-58%), electric fan (0-36%) and air conditioner (0-6%).

In 2050, the pre-event critical daily maximum peak demand is estimated to be 3208 MW, a 56% increase in 2030. The DR event period caused an averaged critical peak demand reduction varying between 65 MW and 406 MW (2-14%) for all scenarios. Scenario 6 was the highest while scenario 1 is the lowest. The contribution of appliances to the reduced peak demand varied; washing machine (0-52%), electric iron (0-48%), electric boiler (nearly 0%), refrigerator (0-60%), electric fan (0-33%) and air conditioner (0-7%).

In summary, the results show a substantial potential of evening peak

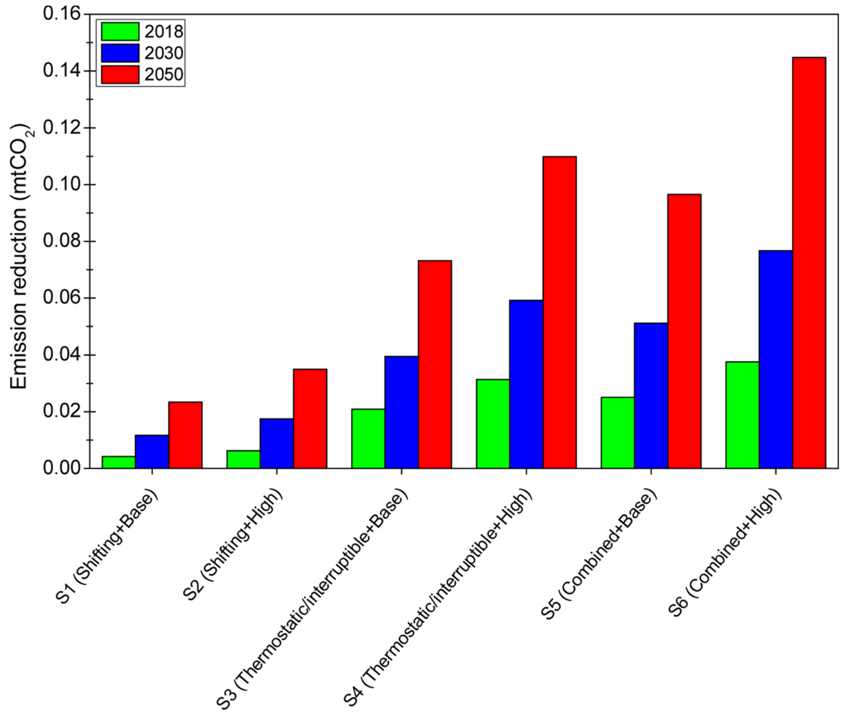

Fig. 10. Annual emissions reduction.

load reduction on the grid network through households' demand response and the percentage demand reduction is comparable to a global range of 0-14% (Carroll et al., 2014). With only load shifting as a DR strategy and high household willingness in DR participation, a savings of 98 MW could be realized by 2050 with the least of investment. This strategy alone has the potential of postponing the construction of a greenfield peak-based thermal plant with higher investment and operational costs. The findings are similar to already existing studies and further confirms the impact of voluntary demand response. A case study conducted by Gyamfi and Krumdieck (2011) for the residents of Christchurch, New Zealand indicated that through voluntary demand response, load shifting or shedding reduced morning and evening peak by 10% and 7% respectively. A related study by Fulhu et al. (2019) demonstrated that a 2 hour voluntary demand response signal sent to 25% of the population of Fenfushi village island, Maldives resulted in 10% generator fuel savings during peak periods. To actualize this potential, household electricity users need to be assisted with information on supply security limitations while educating and incentivizing them to reduce demand during peak hours especially in the evenings. The timely delivery of information is key as it can help shape the opinion of residential consumers (Gyamfi & Krumdieck, 2011). Even though, the benefits of demand response to consumers are enormous including financial but the environmental aspect in relation to emission reductions should be communicated sufficiently. When consumers get more engaged and become aware of the importance of living smart and in a more sustainable way, general appeal for the purchase and use of smart appliances could be upheld.

3.4. Emission analysis

Ghana like other parts of Africa are susceptible to the impact of climate change like drought even though they contribute little ($<0.1\%$)[2] to global greenhouse gas emissions. Peak technologies that run on fossil-based fuels contribute to emissions and any reduction in peak demand has the tendency to reduce the aggregate national emission footprint. Fig. 10 shows the cumulative annual carbon dioxide (CO_2) emissions savings from all the scenarios as a result of the reduced critical peak demand. In 2018, the emission savings varied between 0.0042 and 0.0380 million tons of CO_2 ($mtCO_2$). Scenarios 1 and 6 had respectively, the lowest and the highest emission reductions. For all scenarios, the emission savings ranged, 0.0117-0.0770 $mtCO_2$ by 2030 while in 2050 it varied between 0.0233 and 0.1450 $mtCO_2$. The savings over the years are quite substantial and when emission restrictions are applied, it can provide an opportunity for earning carbon credits for Ghana.

3.5. Economic analysis

The net present value was used to measure the economic performance and cost-effectiveness of the scenarios over the entire model time span. The NPV of all scenarios was above zero, meaning investments in any of the demand response actions could fetch a reasonable economic benefit over a period of time. The NPV ranged from 28-645 million US$ over the model period as shown in Fig. 11 with scenario 6 (S6) being the highest and followed in descending order with scenario 1 (S1) being the lowest, relatively. A cursory look at the cumulative free cash flow shows that S1&S2 reaches a break-even point (payback period) after 22 years of implementation of the DR program while S3&S4 and S5&S6 are 15 and 13 years respectively. This suggests that the model time span used for analyzing the economic viability of the DR program is adequate as shorter time might skew the justification for the investment in the DR infrastructure although an excessively long period can have a potential of dismissing possible future risks (e.g. advancement in DR programs and technologies). This finding is instructive as it justifies the economic merit for utility providers to invest in demand response programs as it delays the building of new peak technology power plants and recuperates the returns that go with investment. Aside from the continuous investments, *inter alia,* the initial capital required to implement DR is relatively lower or more affordable than building peak technology plants while the pace on the investment returns is relatively quick. On the part of the consumers, a simple calculation

[2] https://en.wikipedia.org/wiki/List_of_countries_by_greenhouse_gas_emissions

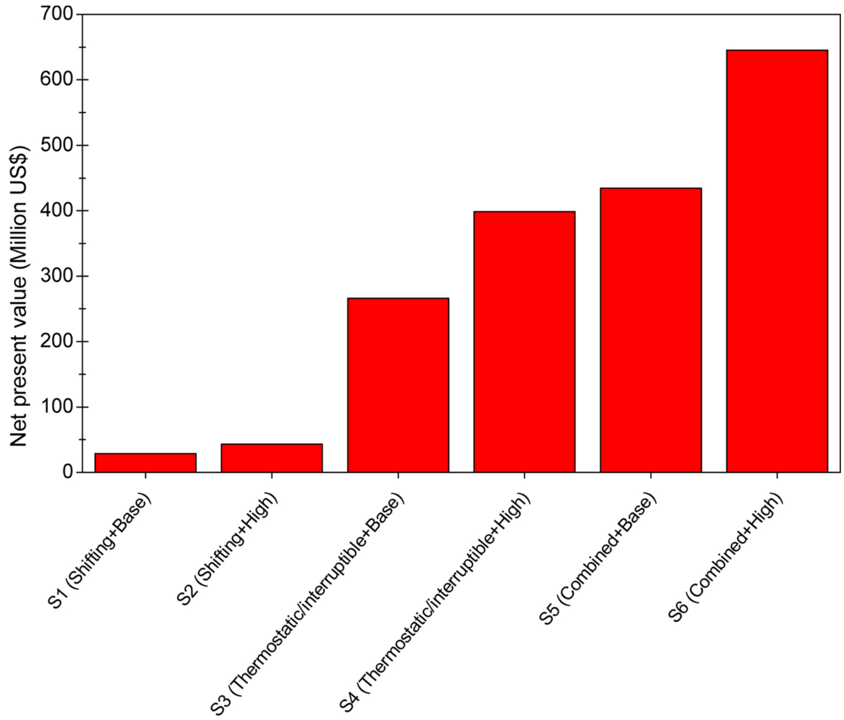

Fig. 11. The net present value for the scenarios.

reveals that using a flat tariff rate of 0.175 US$/kWh (Energy Commission, 2018b) with corresponding annual peak electricity consumption reduction results in electricity bill savings ranging from 0-11 US$/household/year for all scenarios without any additions in financial incentives from the utility providers. The zero bill savings are from the load shifting scenario since there is no tariff difference between on and off-peak period (flat tariff regime) and load shifting usually do not result in savings in electricity consumption. Economic savings can be fully realized through effective cooperation between end-users and utility providers while making efforts to balance the benefits between them.

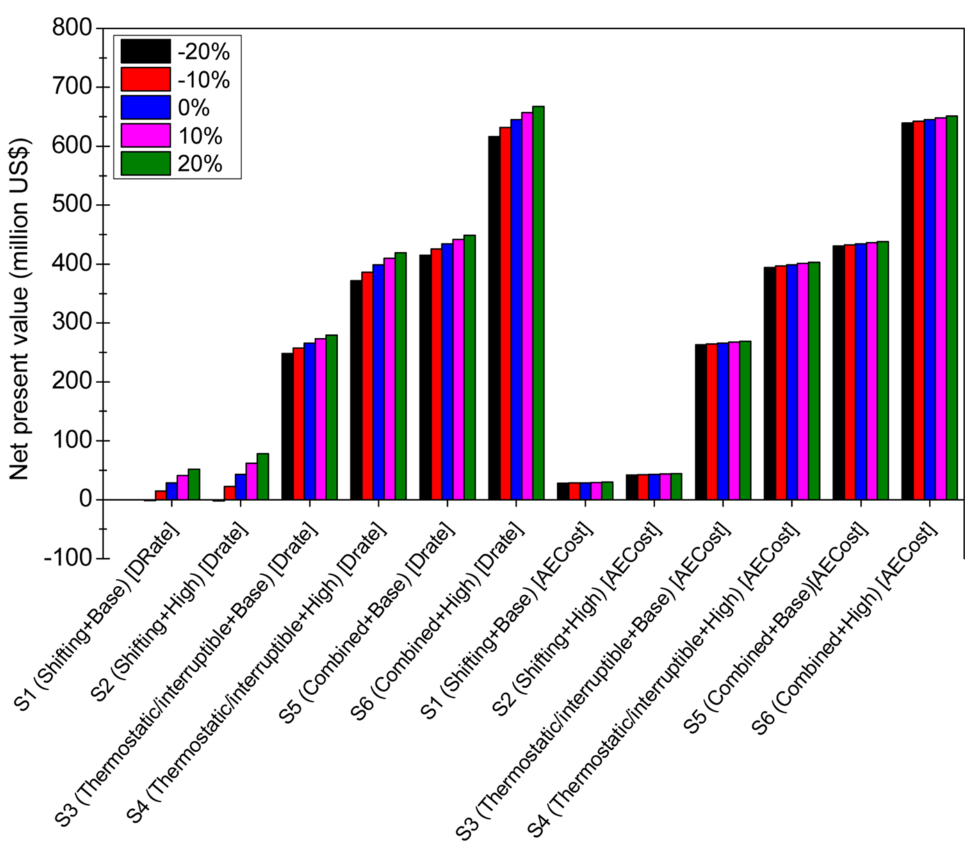

Fig. 12. Sensitivity analysis on NPV based on discount rate (DRate) and avoided emission cost (AECost).

3.6. Sensitivity analysis

A sensitivity analysis is performed in relation to net present value, rebound effect and the payback effect and discussed below.

3.6.1. Sensitivity analysis on the net present value

The sensitivity analysis evaluates how selected decision variables, discount rate and avoided emission cost affects the NPV in the DR economic analysis. The discount rate is chosen to analyze the impact and account for the volatilities in the financial environment while the emission cost is used to canvass the opportunity for decarbonization. Each of the variables is changed between -20% and +20% of the base value, and the effect of the change on the NPV is calculated as presented in Fig. 12. The results indicate that changes in the variables cause variations in the NPV. A decrease of 20% in the discount rate causes a negative NPV for S1&S2, meaning at that rate, it is not economically viable for investment. Aside from that, all the other scenarios show a positive NPV. The difference in NPV from the base value with respect to the discount rate for S1&S2 vary from -105% to 43%, S3&S4 is -7% to 5% while S5&S6 is -4% to 3%. For the avoided emission cost variable, the base value varies for S1&S2 by -3% to 3%, S3&S4 by -1% to 1% and S5&S6 by -1% to 1%. This indicates that a change in the value of the selected variables causes a relative variance in the NPV with the discount rate having the highest impact.

3.6.2. Sensitivity analysis on rebound effect

A sensitivity analysis on a possibility of rebound effect in the use of the controllable appliances is evaluated assuming participating consumers change their lifestyle and tend to purchase a much bigger high performing appliance with relatively higher power utilization. A 10% increase in the diversified household peak demand of each controllable appliance for the year 2030 is assumed in the baseline scenario before and after the DR event. The result for the aggregated hourly load curve for the baseline scenario is compared with and without rebound effect as presented in Fig. 13. The results on a comparative basis show that with rebound effect, the average hourly demand is increased by 8%. This suggests that negative changes in consumer behavior can have the tendency to upsurge in demand for energy services, therefore, it needs to be taken seriously in policy appraisal. To sustainably recoup the benefits of demand response, effective policies on the rebound effect should be developed concurrently with demand side management policies to avoid possible system peak hikes.

3.6.3. Sensitivity analysis on payback or snapback effect

The payback or snapback effect is the increase in the demanded energy in the hours immediately after a demand response event. This occurs usually in cooling and heating thermostatic appliances during their cycling operations. The space temperature drifts up during a demand response event and once the event ends, the system tries to return the space temperature back to its original set point. A sensitivity analysis is conducted to assess its impact on the load demand curve after the DR event. A 10% increase in the consumption of the thermostatic appliances (electric boiler, refrigerator and air conditioner) during off-peak hours is assumed to compensate for the payback effect. The thermostatic controlled/interruptible DR strategy scenario is used and the results compare the impact of payback effect and no payback effect for the load demand for a typical day in 2018, 2030 and 2050 as presented in Fig. 14. There is a relative percentage difference in the hourly energy consumption but the overall average daily energy consumption for all years is increased by 0.13%.

3.7. Policy implications

There are continuous discussions and arguments about the role that demand response is likely to play in the future. Many of such discussions converge and broadly agree that DR is beneficial and complements the various solutions to the eminent energy policy challenges. Though DR initiation is paramount, some challenges still exist in its policy development framework and implementation which needs to be tackled. Several reasons can be identified and associated with a specific DR scheme challenge some of which are discussed next.

3.7.1. Lack of smart metering and ICT infrastructure

Within the smart grid environment, advanced metering, control methods, information and communication technology infrastructure are critical foundation for supporting the implementation and operation

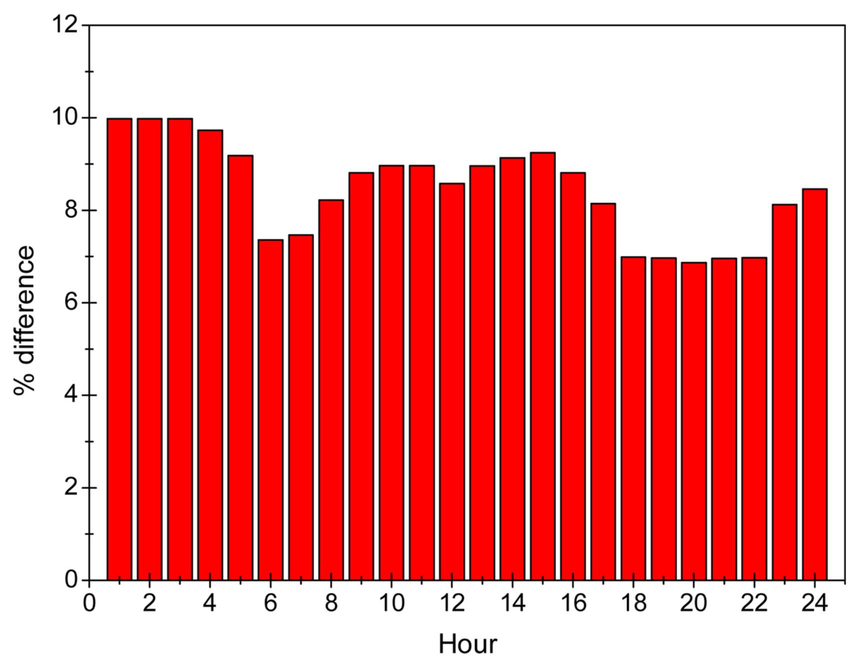

Fig. 13. Sensitivity analysis of rebound effect on aggregate load curve.

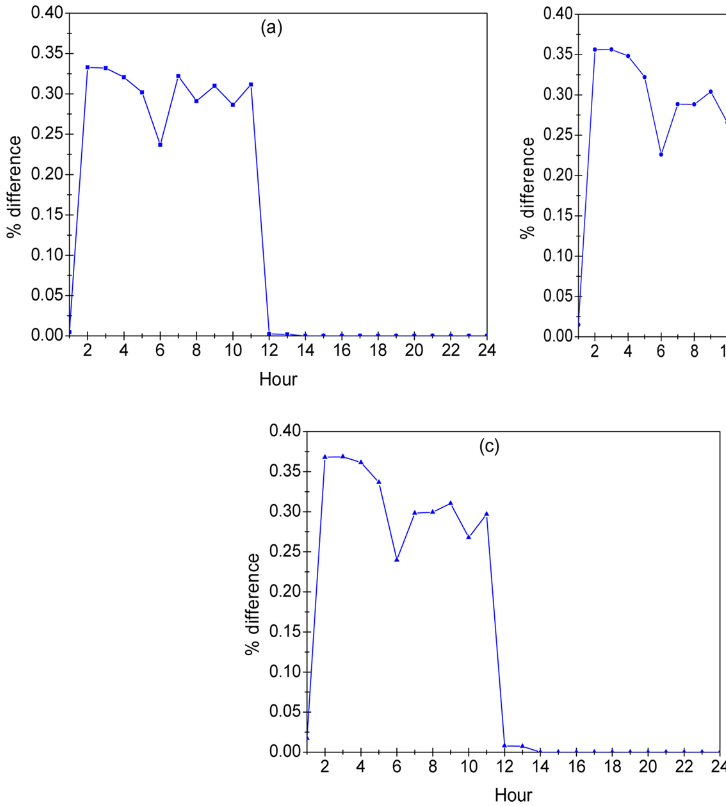

Fig. 14. Sensitivity analysis of the payback effect on hourly load for (a) 2018 (b) 2030 and (c) 2050.

of DR. The smart grid setup is anchored on four main components which include the advanced metering infrastructure, asset management system, advanced transmission and distribution systems (Zhou & Yang, 2015). The advanced metering infrastructure to a large extent supports the implementation of demand response programs while enhancing the interaction between the grid network and the consumers. The advanced metering also aids in improving consumer service, power theft monitoring, power quality and outage management, remote connection and upgrade of meter firmware (Zhou & Yang, 2015). The use of ICT in the control of electricity network systems often leads to the development of an integrated electrical and communication system architecture in the power industry which delivers both electricity and information that controls it (Strbac, 2008). These sophisticated infrastructure costs and its related technical issues are of a major challenge to the implementation of DR programs. The technical challenges related to the ICT side include information security, ICT interoperability, information network management and algorithm stability (Zhou & Yang, 2015). Gradual and sustained investments in the transmission and distribution network will off-set some of the mentioned challenges which will provide the necessary information needed to adequately control remotely flexible loads whenever needed to maintain grid stability

3.7.2. Lack of understanding of the benefits of DR

The involvement of consumers with different behavior, their acceptance and motivation are germane to the successful implementation of DR. The understanding and opportunities of DR programs by consumers during the initial phase is mostly not comprehensive and hence becomes a barrier for their effective participation. Many types of research in behavioral economics have indicated that simply providing consumers with information is not enough to increase their engagement in DSM programs. An example is found with the intervention in the market transformation of compact fluorescent lamps (CFL) in Hungary where a high level of consumer awareness did not necessarily translate into market success. The decision-making process of people is influenced by family, friends, neighbors and social norms. Dawnay & Shah, (2011) in Warren (2015) argued that people are “bad at computation” and are rather driven by other people’s behavior, habits, doing the “right thing”, self-expectations of behavior, being loss-averse and needing to feel involved in making a change. Ponnaganti, Pillai, and Bak-Jensen, 2018) suggest that since consumers especially the residential ones usually are resistant to programs that require effort, focusing first, education and awareness programs on large consumers allow other consumers to assess the rewards and costs associated in participating in DR programs. In line with influencing the behavior of consumers towards changing their energy consumption, behavioral habits, lifestyle and cultural background should be taken into consideration. The government and the utility companies could enhance their advocacy efforts for energy users on the benefits of DR programs in boosting energy efficiency, cost reduction, reliability of grid network, emission reduction, etc.

3.7.3. Lack of market structure and incentives

In implementing DR, the government’s role is critical especially in Ghana where the power industry is not fully and properly deregulated particularly in the distribution sector. Deregulation is thus essential, and more market-oriented policies are critical to stimulating the active participation of utilities and energy consumers in DR programs. Electricity market liberalization sparks up incentive-based strategies for DR implementation. Proper market liberalization ensures the privatization of the power industry to create competition in the market. Market liberalization helps move from vertically-integrated monopolies to retail competition with the consumer having the choice to select their energy supplier. Integrated Resource Planning (IRP) has been argued that it is theoretically suitable and partly applicable in the open market but it is gradually being established that other frameworks for developing DSM, such as energy services and energy efficiency goals are more beneficial (Warren, 2015). IRP refers to a long-term planning process that permits utility entities to compare invariably the cost-effectiveness of all resource alternatives on both the demand and supply side, taking into account their different environmental, financial and reliability characteristics (Al-enezi, 2010). An economic barrier to the DR implementation is the limitation of incentives for utilities to invest in DR especially in a market environment where revenues of utilities traditionally rely on the quantity of electricity sold if there are no financial returns (De la Rue du Can, Leventis, Phadke, & Gopal, 2014). The government ought to play a regulatory role and financial support in the early stage of DR implementation.

The Energy Commission of Ghana is the regulating body of the government responsible for developing regulation, planning and setting policy procedures that address energy issues in the country (Gyamfi et al., 2018). As such, it is the starting point for developing legislation to enhance and motivate efficient use of energy to address peak demand challenges. The engagement of all stakeholders including; utility providers, appliance importers/manufacturers, consumers and policy-makers is needed to develop strategies to address the bottlenecks that limit the acceptance of demand response by these same actors.

4. Conclusions

Demand response is envisaged to play a critical role in balancing electricity supply and demand in the face of fossil fuel resource scarcity and climate change vulnerabilities. Opportunities from residential voluntary demand response are largely unexploited in Ghana and most African countries due to lack of relevant household electricity consumption data, consumer behavior information and detailed economic analysis for implementing such programs. This study combines a questionnaire-based household survey information and measured electricity consumption of household appliances to assess residential demand response potential in Ghana. A bottom-up end-use model is used to develop an aggregate hourly load curve. Electricity consumption is subsequently characterized and categorized in relation to their degree of control to determine peak demand reduction potential. The estimated hourly maximum demand curve of the households is validated with typical national aggregate multi-sectoral daily load profile measured by the grid operator.

Results show that in addition to price, motivating factors such as energy security and environment signals can influence end-users electricity use behavior. It was found that about 90% of average peak demand of the generated residential load curve is contributed by lighting and 4 appliances namely; refrigerator, television, electric fan and air conditioner. The expected average daily peak hour demand reduction from the six scenarios ranged from 65 MW to 406 MW representing 2-14% by 2050. The economic evaluation of the voluntary residential demand response showed that for all scenarios, it was economically viable to invest in DR programs as financial investment with NPV varying between 28-645 million US$ could be recovered within a payback period of 13-22 years of implementation. The study also shows that to actualize energy and cost savings, utility providers and consumers need to cooperate effectively on information delivery and feedbacks while efforts are made to incentivize consumers to balance the benefits between them. Effective information delivery could support consumers to analyze their electricity use, compare and manage their consumption and optimize their use patterns. Residential energy policy development should be innovatively designed to include voluntary demand response and fiscal regimes that support the use of smart appliances and technologies. The sensitivity analysis on the rebound effect shows a relative increase in the average hourly demand and therefore indicates the need to establish tailored rebound mitigating policies.

This study is subject to some limitations. The hourly variation patterns for appliance electricity use were assumed to be the same over the model time horizon but this could change over time due to changes in lifestyle, behavior and socio-economic dynamics. The evolution of appliance ownership could vary with changes in projected growth in urbanization rate, electrification rate and household income levels. The diversified household peak demand is assumed to be the same over the period but changes in appliance energy use regulation could present some future changes. The cost data can vary from one utility provider to another, therefore, cost variations can have a substantial impact on the quantitative results. Future study is recommended to estimate the potential of demand response on peak demand from the commercial and industrial sectors, its impact on future generation expansion and grid stability.

Conflict of interest

None.

Acknowledgments

This work is supported by the Fundação para a Ciência e Tecnologia (FCT) through the MIT-Portugal Program and the FCT scholarship PD/BD/113712/2015. This author is grateful to FCT for financial support. Thanks are also due to FCT through support from the IN+ Strategic Project UID/EEA/50009/2013 and the scholarship SFRH/BPD/96459/2013. Financial support by Deutsche Forschungsgemeinschaft (DFG) within the framework of the Graduate School of Energy Science and Engineering (GSC 1070) at TU Darmstadt is duly acknowledged.

References

Aghaei, J., & Alizadeh, M. I. (2013). Demand response in smart electricity grids equipped with renewable energy sources: A review. *Renewable and Sustainable Energy Reviews, 18*, 64–72. https://doi.org/10.1016/j.rser.2012.09.019.
Al-enezi, A. N. (2010). *Demand Side Management (DSM) For Efficient Use of Energy in the Residential Sector in Kuwait : Analysis of Options and Priorities*.
Avila, N., Carvallo, J. P., Shaw, B., & Kammen, D. M. (2017). *The energy challenge in sub-Saharan Africa : A guide for advocates and policy makers. In oxfam Researcher Background.* https://doi.org/10.13140/RG.2.2.25037.44001.
Bartusch, C., Wallin, F., Odlare, M., Vassileva, I., & Wester, L. (2011). Introducing a demand-based electricity distribution tariff in the residential sector: Demand response and customer perception. *Energy Policy, 39*(9), 5008–5025. https://doi.org/10.1016/j.enpol.2011.06.013.
Bradley, P., Leach, M., & Torriti, J. (2011). *A review of current and future costs and benefits of demand response for electricity. In Energy policy*. United Kingdom: Guildford.
Campillo, J., Dahlquist, E., Wallin, F., & Vassileva, I. (2016). Is real-time electricity pricing suitable for residential users without demand-side management? *Energy, 109*, 310–325. https://doi.org/10.1016/j.energy.2016.04.105.
Carroll, J., Lyons, S., & Denny, E. (2014). Reducing household electricity demand through smart metering: The role of improved information about energy saving. *Energy Economics, 45*, 234–243. https://doi.org/10.1016/j.eneco.2014.07.007.
CBONDS (2018). *Bond issuance rate.* Retrieved October 20, 2018, from http://em.cbonds.com/countries/Ghana-bond.
Conchado, A., Linares, P., Lago, O., & Santamaría, A. (2016). An estimation of the

economic and environmental benefits of a demand-response electricity program for Spain. *Sustainable Production and Consumption, 8*(March), 108–119. https://doi.org/10.1016/j.spc.2016.09.004.
Crundwell, F. K. (2008). *Finance for engineers: evaluation and funding of capital projects.* https://doi.org/10.1007/978-1-84800-033-9.
Dawnay, Emma, & Shah, H. (2011). *"Behavioural Economics: Seven Key Principles for Environmental Policy." The Political Economy of the Environment: An Interdisciplinary Approach, Routledge Studies in Contemporary Political Economy*. London: Routledge74–98.
De la Rue du Can, S., Leventis, G., Phadke, A., & Gopal, A. (2014). Design of incentive programs for accelerating penetration of energy-efficient appliances. *Energy Policy, 72*, 56–66. https://doi.org/10.1016/j.enpol.2014.04.035.
De la Rue du Can, S., Pudleiner, D., & Pielli, K. (2018). Energy efficiency as a means to expand energy access: A Uganda roadmap. *Energy Policy, 120*(January), 354–364. https://doi.org/10.1016/j.enpol.2018.05.045.
Diawuo, F. A., & Kaminski, J. (2017). An analysis of the Ghanaian power generation sector using an optimization model. *Journal of Power Technologies, 97*(1), 15–27 Retrieved from http://papers.itc.pw.edu.pl/index.php/JPT/article/view/506/755.
Diawuo, F. A., Pina, A., Baptista, P. C., & Silva, C. A. (2018). Energy efficiency deployment: A pathway to sustainable electrification in Ghana. *Journal of Cleaner Production, 186*, 544–557. https://doi.org/10.1016/j.jclepro.2018.03.088.
Diawuo, F. A., Sakah, M., Pina, A., Baptista, P. C., & Silva, C. A. (2019). Disaggregation and characterization of residential electricity use: Analysis for Ghana. *Sustainable Cities and Society, 48*(March), 101586. https://doi.org/10.1016/j.scs.2019.101586.
Dranka, G. G., & Ferreira, P. (2019). Review and assessment of the different categories of demand response potentials. *Energy, 179*, 280–294. https://doi.org/10.1016/j.energy.2019.05.009.
Energy Commission (2018a). *Energy supply and demand outlook for Ghana*.
Energy Commission (2018b). *National energy statistics 2008-2017*.
Energy Commission of Ghana (2014). *Energy Supply and Demand Outlook for Ghana.* Retrieved from http://www.energycom.gov.gh/planning/data-center/energy-outlook-for-ghana.
Fulhu, M., Mohamed, M., & Krumdieck, S. (2019). Voluntary demand participation (VDP) for security of essential energy activities in remote communities with case study in Maldives. *Energy for Sustainable Development, 49*, 27–38. https://doi.org/10.1016/j.esd.2019.01.002.
Ghana Statistical Service (GSS) (1995). *Ghana living standards survey : report on the third round (GLSS3) : September 1991 - September 1992*.
Ghana Statistical Service (GSS) (2000). *Ghana Living Standards Survey Round 4 (GLSS4)*.
Ghana Statistical Service (GSS) (2008). *Ghana Living Standards Survey Report of the Fifth Round (Glss 5) (Vol. 113)*https://doi.org/10.1016/j.exppara.2005.11.016.
Ghana Statistical Service (GSS) (2014). *Ghana Living Standards Survey Round 6 (GLSS 6)*.
GRIDCo (2017). *Electricity Supply Plan for Ghana*.
GRIDCo (2018). *Electricity supply plan for Ghana (Vol. 53)*. https://doi.org/10.1017/CBO9781107415324.004.
Gyamfi, S. (2010). *Demand Response Assessment and Modelling of Peak Electricity Demand in the Residential Sector: Information and Communcation Requirements.* UNIVERSITY OF CANTERBURY.
Gyamfi, S., Diawuo, F. A., Nyarko Kumi, E., Sika, F., & Modjinou, M. (2018). The energy efficiency situation in Ghana. *Renewable and Sustainable Energy Reviews, 82*(June 2017), 1415–1423. https://doi.org/10.1016/j.rser.2017.05.007.
Gyamfi, S., & Krumdieck, S. (2011). Price, environment and security: Exploring multimodal motivation in voluntary residential peak demand response. *Energy Policy, 39*(5), 2993–3004. https://doi.org/10.1016/j.enpol.2011.03.012.
Gyamfi, S., & Krumdieck, S. (2012). Scenario analysis of residential demand response at network peak periods. *Electric Power Systems Research, 93*, 32–38. https://doi.org/10.1016/j.epsr.2012.07.004.
Haghifam, S., Dadashi, M., Zare, K., & Seyedi, H. (2020). Optimal operation of smart distribution networks in the presence of demand response aggregators and microgrid owners : A multi follower Bi-Level approach. *Sustainable Cities and Society, 55*(December 2019), 102033. https://doi.org/10.1016/j.scs.2020.102033.
Hamidi, V., Li, F., & Robinson, F. (2009). Demand response in the UK's domestic sector. *Electric Power Systems Research, 79*(12), 1722–1726. https://doi.org/10.1016/j.epsr.2009.07.013.
IEA (2017). *National electricity consumption data of Ghana. Retrieved March 20, 2017, from International Energy Agency (IEA)*website: http://www.iea.org/statistics/statisticssearch/report/?country=Ghana&product=electricityandheat.
IEA (2019b). *Africa Energy Outlook 2019*.
IEA (2019a). *World Energy Outlook 2019*Retrieved from https://www.iea.org/reports/world-energy-outlook-2019.
Konstantelos, I., Sun, M., & Strbac, G. (2014). *Quantifying demand diversity of households.* Retrieved from https://spiral.imperial.ac.uk/bitstream/10044/1/30567/2/LCL ICL Quantifying Demand Diversity of Households FINAL.PDF.
Lynch, M., Nolan, S., Devine, M. T., & O'Malley, M. (2019). The impacts of demand response participation in capacity markets. *Applied Energy, 250*(December 2018), 444–451. https://doi.org/10.1016/j.apenergy.2019.05.063.
Malik, A., Haghdadi, N., MacGill, I., & Ravishankar, J. (2019). Appliance level data analysis of summer demand reduction potential from residential air conditioner control. *Applied Energy, 235*(October 2018), 776–785. https://doi.org/10.1016/j.apenergy.2018.11.010.
McNeil, M. A., & Letschert, V. E. (2010). Modeling diffusion of electrical appliances in the residential sector. *Energy and Buildings, 42*(6), 783–790. https://doi.org/10.1016/j.enbuild.2009.11.015.
McNeil, M. A., Letschert, V. E., de la Rue du Can, S., & Ke, J. (2013). Bottom-Up Energy Analysis System (BUENAS)-an international appliance efficiency policy tool. *Energy Efficiency, 6*(2), 191–217. https://doi.org/10.1007/s12053-012-9182-6.
Mims, N., Eckman, T., & Schwartz, L. (2018). *Time-varying value of energy efficiency in Michigan.* Berkeley, California, USA.
Ouedraogo, N. S. (2017). Modeling sustainable long-term electricity supply-demand in Africa. *Applied Energy, 190*, 1047–1067. https://doi.org/10.1016/j.apenergy.2016.12.162.
Parrish, B., Heptonstall, P., Gross, R., & Sovacool, B. K. (2020). A systematic review of motivations, enablers and barriers for consumer engagement with residential demand response. *Energy Policy, 138*(December 2019), 111221. https://doi.org/10.1016/j.enpol.2019.111221.
Piette, M. A., Schetrit, O., Kiliccote, S., Cheung, I., & Li, B. Z. (2015). *Costs to automate demand response - taxonomy and results from field studies and programs*Retrieved from https://gig.lbl.gov/sites/all/files/drrc_final_report_taxonomy.lbnl-1003924.pdf.
Ponnaganti, P., Pillai, J. R., & Bak-Jensen, B. (2018). Opportunities and challenges of demand response in active distribution networks. *Wiley Interdisciplinary Reviews: Energy and Environment, 7*(1), https://doi.org/10.1002/wene.271.
Ruble, I., & Karaki, S. (2013). Introducing mandatory standards for select household appliances in Lebanon: A cost-benefit analysis. *Energy Policy, 52*, 608–617. https://doi.org/10.1016/j.enpol.2012.10.016.
Saidur, R., Masjuki, H. H., Jamaluddin, M. Y., & Ahmed, S. (2007). Energy and associated greenhouse gas emissions from household appliances in Malaysia. *Energy Policy, 35*(3), 1648–1657. https://doi.org/10.1016/j.enpol.2006.05.006.
Sakah, M., De la Rue du Can, S., Diawuo, F. A., Delight, M., & Kuhn, C. (2019). A study of appliance ownership and electricity consumption determinants in urban Ghanaian households. *Sustainable Cities and Society, 44*(August 2018), 559–581. https://doi.org/10.1016/j.scs.2018.10.019.
Sakah, M., Diawuo, F. A., Katzenbach, R., & Gyamfi, S. (2017). Towards a sustainable electrification in Ghana: A review of renewable energy deployment policies. *Renewable and Sustainable Energy Reviews, 79*(February 2016), 544–557. https://doi.org/10.1016/j.rser.2017.05.090.
Shen, B., Ni, C. C., Ghatikar, G., & Price, L. (2012). *What China can learn from international experiences in developing a demand response program. ECEEE 2012 SUMMER STUDY ON ENERGY EFFICIENCY IN INDUSTRY, (June), 419–428*.
Soares, A., Gomes, Á., & Antunes, C. H. (2014). Categorization of residential electricity consumption as a basis for the assessment of the impacts of demand response actions. *Renewable and Sustainable Energy Reviews, 30*, 490–503. https://doi.org/10.1016/j.rser.2013.10.019.
Srivastava, A., Van Passel, S., & Laes, E. (2019). Dissecting demand response: A quantile analysis of flexibility, household attitudes, and demographics. *Energy Research and Social Science, 52*(October 2018), 169–180. https://doi.org/10.1016/j.erss.2019.02.011.
Staats, M. R., de Boer-Meulman, P. D. M., & van Sark, W. G. J. H. M. (2017). Experimental determination of demand side management potential of wet appliances in the Netherlands. *Sustainable Energy, Grids and Networks, 9*, 80–94. https://doi.org/10.1016/j.segan.2016.12.004.
Strbac, G. (2008). Demand side management: Benefits and challenges. *Energy Policy, 36*(12), 4419–4426. https://doi.org/10.1016/j.enpol.2008.09.030.
Thakur, J., & Chakraborty, B. (2016). Demand side management in developing nations: A mitigating tool for energy imbalance and peak load management. *Energy, 114*, 895–912. https://doi.org/10.1016/j.energy.2016.08.030.
Torriti, J. (2012). Price-based demand side management: Assessing the impacts of time-of-use tariffs on residential electricity demand and peak shifting in Northern Italy. *Energy, 44*(1), 576–583. https://doi.org/10.1016/j.energy.2012.05.043.
Turan, G. (2014). *Electric Power Distribution System Engineering* (3rd ed.). Taylor & Francis Group.
Ueno, T., Inada, R., Saeki, O., & Tsuji, K. (2006). Effectiveness of an energy-consumption information system for residential buildings. *Applied Energy, 83*(8), 868–883. https://doi.org/10.1016/j.apenergy.2005.09.004.
United Nations (2015). *World Population Prospects: The 2015 Revision, Key Findings and Advance Tables. Working Paper No. ESA/P/WP.241. In United Nations, Department of Economic and Social Affairs, Population Division (Vol. 1)*. https://doi.org/10.1017/CBO9781107415324.004.
Vanthournout, K., Dupont, B., Foubert, W., Stuckens, C., & Claessens, S. (2015). An automated residential demand response pilot experiment, based on day-ahead dynamic pricing. *Applied Energy, 155*, 195–203. https://doi.org/10.1016/j.apenergy.2015.05.100.
Vivian, J., Chiodarelli, U., Emmi, G., & Zarrella, A. (2020). A sensitivity analysis on the heating and cooling energy flexibility of residential buildings. *Sustainable Cities and Society, 52*(July 2019), 101815. https://doi.org/10.1016/j.scs.2019.101815.
Warren, P. (2015). *Demand-Side Management Policy : Mechanisms for Success and Failure*.
Wohlfarth, K., Worrell, E., & Eichhammer, W. (2020). Energy efficiency and demand

response – two sides of the same coin? *Energy Policy, 137*(October 2019), 111070. https://doi.org/10.1016/j.enpol.2019.111070.
Woolf, T., Malone, E., Schwartz, L., & Shenot, J. (2013). *A Framework for Evaluating the Cost-Effectiveness of Demand Response National Forum of the National Action Plan on Demand Response*.
World Bank (2017). *World bank development indicators.* Retrieved February 11, 2017, from http://databank.worldbank.org/.
Xiang, Y., Cai, H., Gu, C., & Shen, X. (2020). Cost-benefit analysis of integrated energy system planning considering demand response. *Energy, 192*, 116632. https://doi.org/10.1016/j.energy.2019.116632.
Yahia, Z., & Pradhan, A. (2020). Multi-objective optimization of household appliance scheduling problem considering consumer preference and peak load reduction. *Sustainable Cities and Society, 55*(1410), 102058. https://doi.org/10.1016/j.scs.2020.102058.
Zhou, K., & Yang, S. (2015). Demand side management in China: The context of China's power industry reform. *Renewable and Sustainable Energy Reviews, 47*, 954–965. https://doi.org/10.1016/j.rser.2015.03.036.