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Optimizing sheddable and shiftable residential electricity consumption by incentivized peak and off-peak credit function approach

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HIGHLIGHTS

- A credit function as a virtual price is introduced to our model.
- Simulation results of 3 cases for its application to residential end-users are considered.
- The simulation results indicate the need to create a balance between consumers' interest and retailers' interest.

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ABSTRACT

Many current studies on smart grid in electricity market are indicative of the key role it plays in electricity generation, distribution, retailing and end-user management. Demand response programs (DRPs) can be used to lower high energy prices in wholesale electricity markets, and ensure the security of power systems when at risk. The concern of most researchers in this field is to further unearth the potential of smart grid in the direction of demand response (DR) through enhanced demand side management (DSM) centering on the behavior of the end-user. Our model proposes a more effective way in using incentive based demand response program to help residential customers derive more benefits from smart grid. The constrained non-linear programming (CNLP) model optimizes residential consumption of electricity by shaving of load at peak and increasing of load at off-peak to help generators reduce production cost at peak times and increase revenue at of off-peaks. The model uses a credit function to regulate consumption and reward end-users for load shedding and load shifting at peaks and also at off-peaks reward end-users for increasing load. The simulated results show that, high consumption appliances are best used at dawn, midday, and at night, if consumers want to cut down cost. The corresponding effect is that, generating and distribution companies derive the right revenue from their investments by not producing beyond their capacity during peaks at high cost and maintain constant power supply in and environmentally friendly manner.

1. Introduction

The generation of power at an affordable pricing has been the concern of power producing companies and industries in this era of global concerns against the effects of climate change and global warming. As a result, many attempts have been made by various studies to design effective and efficient programs that help to produce power and prudently manage its usage in both industrial and commercial ventures as well as in residential activities [1,2]. Most recent research works in the field of electricity production and its management focuses on the cost associated with power generation, distribution and utilization aimed at minimizing production cost and maximizing profit alongside minimizing consumers cost of utility with maximum satisfaction. Since these two parties are major stakeholders in the electricity market, their interests are of utmost concern to most researchers whose studies encompasses finding a balance between end-user consumption within grid generation capacity limits and affordable pricing at peaks, in an environmentally friendly manner in this era of climate change challenges.

Smart grid has brought much relief to stakeholders and reduced a lot of challenges in power management but more needs to be done to ensure producers and consumers get the best from the electricity power market [3–5]. One of such reliefs to customers is the ability to prudently manage utility to avoid high tariffs at peaks when electricity tariffs are

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Nomenclature

CNLP	constrained non-linear programming
CPP	critical peak price
CPPLC	critical peak pricing with load control
DOE	department of energy
DR	demand response
DRMC	demand response management
DRP	demand response program
DSM	demand side management
FERC	federal energy regulatory commission
HEM	home energy management
HVAC	heating, ventilation and air-conditioning
LSE	load serving entity
PV	photo-voltaic
RES	renewable energy source
RTP	real time price
SCUC	security constraint unit commitment
SQP	sequential quadratic programming
TOU	time of use

Parameters

λ	weight assigned to the right part of our objective function to alter participation level in the DR program and assess performance of our model
Lb_c^{P2}	lower limit consumptions for sheddable load for customer c at time t
Ub_c^{P2}	upper limit consumptions for sheddable load for customer c at time t
Lb_c^{P3}	lower limit consumption for shiftable load for customer c at time t
Ub_c^{P3}	upper limit consumption for shiftable load for customer c at time t
t	index for time
c	index for customer or end-user
n	total number of customers
E_c^-	minimum total load a consumer can use for a day
E_c^+	maximum load a consumer can enjoy for a day
Maxload(t)	total initial load of all customers at time t
K	payment coefficient
α	amplitude of the utility function
β	rate at which a consumer's utility increases to attain satisfactory level
ϕ	indicator that determines whether a customer is eligible for credit
P2	sheddable load category
P3	shiftable load category
A	total discount given to consumers by policy implementer
A_1	discount for peaks
A_2	discount for off- peaks

Variables

$U(d_c(t))$	utility cost to customer c for consuming load of dc(t)
$d_c(t)$	optimal load for customer c at time t
$p_c(t)$	new price attained by customer c for taking part in the scheme
$d_{0c}(t)$	initial load for customer c at time t
$p_{0c}(t)$	initial price for customer c at time t
$d_c^{P1}(t)$	non-sheddable load of customer c at time t
$d_c^{P2}(t)$	sheddable load of customer c at time t
$d_c^{P3}(t)$	shiftable load of customer c at time t
$Credit_c(t)$	incentive gained by customer c at time t
$d_{0c}^{P2}(t)$	initial non-sheddable load of customer c at time t
$d_{0c}^{P3}(t)$	initial shiftable load of customer c at time t
$\overline{D}$	total average load for all consumers
$\Delta p_c(t)$	price change for customer c at time t
τ_1	peak times
τ_2	off-peak times

high. This helps cut down on their consumptions at peaks whenever possible. This reduces the demand at peaks which saves electricity producing companies from high production cost at critical peaks and helps in the reduction of excessive carbon emission into the atmosphere by power generating industries. Smart grid provides power operators with reliable data and information which guides them in their decision making regarding their operations, network setup and distribution. In this era of digital systems, smart grid distribution network system effectively help in solving the challenges of customers, ensuring reliable supply of power and swift adherence to end-users needs in an environmentally friendly condition [6]. Power producing and distributing companies via smart grid know every customers load (consumption) at any time. Smart meters ensures that only consumers using more utility at peak times pay for their usage freeing other users from sharing in their payment if the case were to be a flat rate scenario [7,8].

Demand response DR is a term defined as changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized by the U.S. Department of Energy (DOE) and comprises incentive-based programs and price-based programs (time-of-use, critical peak pricing, dynamic pricing) [9–13]. Consumers through smart grid are updated with timely data and information on electricity tariffs [14]. In conjunction with communication network systems, smart grid metering system has significantly improved various demand response programs, which has helped consumers save cost and indirectly helped improve the environment as well [6]. In a smart grid, the responsibility of stakeholders in the electricity production business is to modify the integration of distributed renewable resources, energy-efficiency services, local balancing, smart energy systems and large volumes of information. At the customer level, distribution system operators are doing their best to provide their customers with high level reliable and quality services through optimal planning [6,15].

Smart grid and deregulated power systems differ, in that, the transmission of data and information which is bilateral, and the decision made by the network for the provision of their demand is done well and timely, whereas by contractual agreement, the electricity distributing systems manages the power of the customer with smart grid sending and receiving data and information. The basic structure of deregulated power system without smart grid can price electricity for varying times but does not offer the requisite capabilities for handling a variety of arrangements between the power producing company and its customers [16,17].

Providing grid reliability and market efficiency which has become the focus of many research works is the issue of DR. DR has gained the attention of most researchers in this field because of its assurance of achieving grid reliability and market efficiency results [18]. This possibility depends on the type of service, placement in the network, availability, flexibility and time for it to be operational in smart grid. Incentive-based DR programs compensate customers for participating in the flexibility provision. Price-based DR programs has price varying components which are indicative of timely market and grid situations of which real-time pricing (RTP), time of use (TOU) and critical peak pricing (CPP) are part [19]. Electricity producing companies refer to the use of their network as consumption (electricity requisition), generation (electric power injection) and presumption (combined requisition and injection).

Distribution network systems have the following key charges; (1) the primary network connection charge; (2) the required level of network tariffs (use-of-system charge) for allowed income during regulative period and; (3) the desirable structure of network tariffs, i.e. network charges according customer categories, period of grid use and the mobility of customers when considering distributed energy resources. The primary connection charge becomes serious when connecting your own energy resources since the end-user is obligatory to bear the responsibility for externalities imposed on the grid [6].

DR program improves the conditions of uninterruptible power supply and flexibility in the power markets, leading to promptness, efficiency and performance [20]. It helps end-users to actively participate in the power market to derive the optimal utilization of the smart grid and reward them for prudent usage of utility based on pricing conditions communicated to them. The DR program has a flexible supply feature which is of much concern to stakeholders although it has not been proven to outline its potential savings that can be derived in the electricity value market chain [8,21]. There are has been extensive work done in recent times by various scholars in this area of DR covering the operations of generators, distributors, retailers and consumers all in a bit to unearth more and more benefits to stakeholders in the electricity market. Aghaei and Alizadeh [22] investigated DR considering CPPLC in a cost-emission-based unit commitment problem using a modified ϵ-constraint multi-objective optimization method. Their study showed that, multiple desired results is simultaneously achievable in DR program when we consider multi-objectives function which encompasses the operations of generators which impacts significantly on price and demand which are cost of generation and mode of generation.

Work of Aghaei et al. [9] looked at the contribution of DRPs in power system reliability by investigating the influence of emergency demand response programs in improving power reliability in case of failure of generation units. Their objective was aimed at improving the social benefits and reliability indicators by verifying the efficiency of integrating DRPs to the SCUC problem. Their results indicated that, improving social welfares for consumers is good in the wholesale electric market and can be used to provide benefits for demand side consumers by being rewarded in return for their load reduction. This is in-line with our study which focuses on consumers load (sheddable and shiftable) and introduce a credit function to reward them for peak time load shedding and load shifting, as well as off-peak increment of load. According to Aghaei et al. [9] reliability may also be improved by reducing very expensive involuntary load shedding during peak times. Their study also revealed that, demand versus price parameters influence greatly load reduction decision making.

From the studies of Erdinc et al. [23], remarkable potential exists for the application of DR programs for a number of purposes which includes peak load shaving, frequency regulation, etc., by using thermostatically controllable appliances. They aimed at minimizing the average deviation from of household temperature values of group of contracted residential end-users during a DR event, alongside meeting load reduction goals of LSE. Their conclusion was that, their strategy proved to have a decrement in violation of end-user comfort level while effectively satisfying the requirement of LSE in terms of load demand reduction. They asserted that, there are numerous areas to which their study can be extended to. Although their study aims at residential end-users and specifically HVAC units, their proposed formulation can be extended to cover a variety of appliance types by additional specifications on comfort violation because of the participation in DR programs. By this, they encouraged future further studies on diversification of DR capacity offered by each end-user type and more specifically by each end-user appliance which aims at more diversified DR enabling appliance scheduling.

Paterakis et al. [24] developed a detailed home energy management system structure which determines the optimal day-ahead appliance scheduling of a smart household under hourly pricing and peak power-limiting (hard and soft power limitation)-based demand response strategies. The aim of their optimization problem was to minimize the total cost to meet the electrical energy needs of the household in a dynamic pricing environment and their model results proved very computationally efficient. Paterakis et al. [25] analyzed the optimal operation of a neighborhood of smart households in terms of minimizing the total energy procurement cost where each household is equipped with at least one of assets such as electric vehicles, controllable appliances, energy storage and distributed generation. It is evident from their work that, apart from the distributed generation unit, technological options such as vehicle-to-home and vehicle-to-grid are available to provide energy to cover self-consumption needs and to inject excessive energy back to the grid, respectively. In their study, a limit is imposed on the total power that may be drawn by the households to prevent power peaks that could jeopardize the transformer. They also resolved potential competitive behavior, especially during relatively low-price periods by proposing a simple strategy to promote the fair usage of transformer distribution capacity. Its application incentivized users to shift their consumption in order to achieve lower electricity bills.

Paterakis et al. [26] assessed the impact of price-based DR strategies on smart household load pattern variations on the background that, changes in load patterns due to demand response (DR) activities at end-user premises, such as smart households, constitute a vital point to be considered both in system planning and operation phases. They used artificial neural networks and wavelet transform to forecast the response of residential loads to different price signal. Their results showed the DR effect on load pattern forecasting, which is a tool useful for market participants such as aggregators in pool-based market structures, or for load serving entities to investigate potential change requirements in existing DR strategies, and effectively plan new ones. They also recommended future studies to be conducted to develop appropriate methods to resolve and deal with the uncertainties in the end-users' behavior. Therefore, the behavior of the end-user has not been fully resolved as regards DR programs and DSM strategies.

In line with the recommendations from previous studies to conduct furthers studies on DSM of DR programs that we propose a scheme, which considers the consumption pattern of residential end-users, limiting it to their shiftable load and sheddable load. In our study we use a constrained non-linear programming (CNLP) framework and introduce a credit incentive function which enable end-user to shave peak load through shedding and shifting of load to gain credit which reflects in lower peak price. Similarly, at off-peaks the credit function encourages them to increase their load to gain credit which reflects in their off-peak prices. The resultant effect is to help end-users to be happy with their bills without putting undue pressure on power retailers and generators for more power at peaks, which can jeopardize the grid system and transformer as indicated by various studies on DR. During off-peaks, end-users are encouraged by incentives to increase their load which assures retailers and power generators good returns on their investment to help them stay in business. Altogether, the optimal solution of our proposed model creates a balance of electricity usage between peaks and off-peaks which brings maximum satisfaction to end-users and good revenue for power retailers and generators. In additions, grid stability is assured and operators can avoid high production cost at peaks as well as embark on expansion. The release of harmful emissions into the environment can be checked effectively to improve global climatic conditions.

In China, real time pricing is not used on the electricity market and smart meters have not been widely introduced on the electricity market of China. Only a few cities have smart meters installed but have not introduced real time pricing. About 40% of power generated is consumed by residential end-users as exist in literature from previous studies, therefore, considering the population of China in the light of demand response is an important issue. Getting DR programs to be rolled out in China is important to the government of China, since it will contribute significantly to the goals of cutting down harmful emissions into the atmosphere considerably. Therefore, our study looks to the viability DR in the context of China and can be extended to other economies and geographical setups with similar conditions as China.

The remaining part of this paper is organized as follows: Section 2 details the optimization method used in the study. In Section 3 the operational optimization and simulation results are shown. Discussions of the results are presented in Section 4 and the conclusion for our study presented in Section 5.

2. Optimization method

Optimization is the term often used for minimizing or maximizing a function. The aim of our objective function is to maximize consumers happiness after paying their electricity bills. We used CNLP framework for our study. The function takes the consumption of a customer which can be partitioned into non-sheddable, sheddable and shiftable loads. The non-sheddable loads for all consumers are the same or similar, therefore for this study our focus is on the sheddable and shiftable load components of residential consumption. These two components are then introduced into the utility function. We introduce a credit based incentive function which rewards consumers for load shaving at peaks, and also reward them at off-peaks for increasing their load [27]. This we do with particular interest in our sheddable and shiftable load components of consumers load which is the focus of our research.

The credit incentive attained by each consumer is a function of their consumption and is used to determine the consumers price change which is a reduced price. Thus, establishing the relation and dependence of price and demand as pertains in demand response modeling. The new price is used to compute the consumer bill. A consumer with a small price change will have a small reduction in price whereas a consumer with a big price change will have an appreciable reduction in price which eventually reflects on the billing records of the consumer. The consumers' new prices are inputted into our objective function to determine the optimal solution that best maximizes the satisfaction or happiness of the customer. Here satisfaction is when a consumer is able to use more utility while cutting down load at peaks and increasing load at off-peaks with regards to sheddable load and shiftable load components.

2.1. Objective function (maximizing)

$$\text{Max} \sum_{c=1}^{n} \sum_{t=1}^{24} [U(d_c(t)) - \lambda p_c(t) d_c(t)] \tag{1}$$

where $d_c(t)$ is the optimal load which we desire customer c to consume indicating load cut down at peak. For off-peak, customer c is expected to increase load to a new $d_c(t)$ which is also an optimal level. $U(d_c(t))$ is the utility cost to customer c for consuming load of $d_c(t)$ which is the optimized consumption. $p_c(t)$ is the new price attained by customer c for taking part in the scheme. This credit attained by customer c is used to generate a reduced tariff rate for customer c. The product of the new price and the optimized load at every time t can be determined for each consumer. λ is the weight assigned to the right part of our objective function to alter participation level in the DR program and assess performance of our model.

The objective function in our study maximizes consumers satisfaction and happiness. It has two parts; the utility part which is on the left side of the subtraction sign and the real payment for shedding load which is on the right part of the subtraction sign. The utility part is the utility that customer has enjoyed and has to pay it does not involve any scheme to reduce cost. The right-side component is what the consumer would pay for voluntarily engaging in the scheme that encourages consumers to shed load at peaks and increase load at off-peaks. The difference in the two components is indicative of whether consumers benefit from the shedding of load or not. A big difference indicates more incentive to customers and greater satisfaction and happiness. By this we do not intend to bring discomfort to consumers by letting them cut down load altogether, but rather shift load to more convenient periods that has lower tariffs. The search for an optimal solution in our study is to enable consumers know when to use more electricity and the best way to save high utility cost. Thus, a higher value for our objective function will be indicative of more customer satisfaction, an optimal load which satisfies their needs and makes them happy.

2.2. Constraints

The constraints for the designed variables are outlined as follows:

$$Lb_c^{P2}(t) \leqslant d_c^{P2}(t) \leqslant Ub_c^{P2}(t) \tag{2}$$

Lb_c^{P2} and Ub_c^{P2} are the lower limit and upper limit consumptions respectively for sheddable load for customer c at time t. Consumers sheddable load for every time t is expected to be within the required consumption range set for that time. This is to ensure that generators get returns to break-even on their investment even at the minimal consumption. In much the same way the upper limit ensures consumer do not demand beyond the limit than will endanger the operations of the generators which cannot guarantee sustainable power supply.

$$Lb_c^{P3}(t) \leqslant d_c^{P3}(t) \leqslant Ub_c^{P3}(t) \tag{3}$$

Lb_c^{P3} and Ub_c^{P3} are the lower limit and upper limit consumptions respectively for shiftable load for customer c at time t. Similarly it expected that consumers maintain their shiftable load within the acceptable range for every time t as required by the electricity generation and distribution companies. It is also help them work within efficient operational level which guarantees continuous uninterruptible supply of power and also sustainable over time.

$$8500 \leqslant \sum_{t=1}^{24} d_c^{P3}(t) \leq 9500, \quad c = 1,2,\ldots,n \tag{4}$$

This indicates the daily lower limit and upper limit consumption for a consumer for shiftable load. Every consumers shiftable load for a day is expected within the specified range. Therefore all household appliances that consume high electricity are to be used in such a way that, within a day a customers total electricity used for those appliances will be within the set limits.

$$E_c^- \leqslant \sum_{t=1}^{24} d_c(t) \leqslant E_c^+, \quad c = 1,2,\ldots,n \tag{5}$$

E_c^- is the minimum total load a consumer can use for a day and E_c^+ is the maximum load a consumer can enjoy for a day. The total optimal load for each customer for a day should be higher than E_c^-, and lower than E_c^+, set for that consumer. The total load of the consumer for each day which is a combination of sheddable and shiftable load should remain within the range set for the day by the distributor. Thus, a consumer for a day can only consume as low as the minimum value set for the whole day or can also consume for the entire day a value which equals the upper limit.

$$\sum_{c=1}^{n} d_c(t) \leqslant (\text{Maxload}(t) * rand(1,1)), \quad t = 1,2,\ldots,24 \tag{6}$$

Maxload(t) is the total initial load of all customers at time t and the rand $(1,1)$ operator enables us to randomize it anytime the program is run to ensure agility of the model to uncertainties. It is expected to be greater than the total optimal load of consumers at time t. That is, for each time t if this scenario is maintained, then the electricity generating and distribution companies can supply more power than the total demand of consumers. This ensures no shortages or outages in the supply of electricity to consumers all the times.

$$\sum_{t=1}^{24} d_c(t)p_c(t) \leqslant K\sum_{t=1}^{24} d_{0c}(t)p_{0c}(t), \quad c = 1,2,...,n \tag{7}$$

$d_{0c}(t)$ and $p_{0c}(t)$ are the initial load and initial price respectively for customer c at time t. K is the payment coefficient and is always lower than prevailing market conditions. It is expected that, the bill of the consumer for partaking in the scheme should less or equal to Kth percentage of the prevailing market cost. K is a predetermined percentage such as 0.94 and ensures that consumers are protected for participating in the scheme, guaranteeing them lower utility cost for their participation. The optimal total cost or bill for a day when a consumer voluntarily participates in shaving peak load and increasing of load at the trough to obtain credit incentive should always be lesser than if they had not.

$$\sum_{t=1}^{24} (d_c^{P1}(t) + d_c^{P2}(t) + d_c^{P3}(t)) < \text{delivered power} \tag{8}$$

d_c^{P1} (t) is the non-sheddable load, d_c^{P2} (t) is the sheddable load and d_c^{P3} (t) is the shiftable load of customer c at time t. Non-sheddable load is fixed and is the basic minimum load needed for survival in every household and is consumed almost every time. They cannot do without it. Sheddable load are not like non-sheddable since it bothers on comfort and affordability. Consumers can at times do without them. Shiftable load is a necessity but their use could be deferred to a later time. The total power delivered or supplied to a consumer per day should be more than the consumers consumption need put together in a day which should comprise the non-sheddable, sheddable and shiftable loads of that consumer. Electricity supply to every customer should exceed the customers total electricity need for a day. This assures consumers of their daily power need without interruption [28,19]. For our study load is a combination of sheddable and shiftable loads, unless otherwise qualified with an adjective.

2.3. Utility function

The utility function used in this study is of the form outlined in [29].

$$U(d_c(t)) = \begin{cases} \alpha(d_c(t))^{\beta}, & d_c(t) > 0, \alpha > 0, \quad 0 < \beta < 1, \\ \alpha^{(1-\beta)}, d_c(t) = 1/\alpha, & \alpha > 0, \quad 0 < \beta < 1. \end{cases} \tag{9}$$

where $U(d_c(t))$ is the utility enjoyed by customer c, at any given time t. $d_c(t)$ is the load of the customer. α is the amplitude of the utility. The bigger the amplitude, the more utility a customer enjoys and the greater the satisfaction of the consumer. The ratio β is the rate at which a consumers utility increases to attain satisfactory level and it lies between zero and one. It is best to kept it closer to zero which is the lower limit so that customers take time to reach satisfactory level. If the rate is higher, then the consumer takes a shorter time to reach satisfactory level. The value of one is not the best since it makes the utility function linear indicating more consumption more satisfaction which cannot be the case or becomes difficult to meet in real sense. Our objective is to maximize the customers utility as well as cutting down on cost to make the consumer happy.

$$U(d_c(t)) = \begin{cases} \alpha(d_c^{P2}(t) + d_c^{P3}(t))^{\beta}, & d_c^{P2}(t) + d_c^{P3}(t) > 0 & \text{at least} d_c^{P2}(t) \\ & & \text{or} d_c^{P3} > 0, \\ \alpha^{1-\beta}, & d_c^{P2}(t) + d_c^{P3}(t) & \text{at least} d_c^{P2}(t) \\ & = 1/\alpha & \text{or} d_c^{P3} > 0, \end{cases} \tag{10}$$

where $d_c^{P2}(t)$ and $d_c^{P3}(t)$ are the sheddable load and shiftable load of customer c, at any time t.

For our study, the electricity consumption of the consumer is referred to as the load and for the utility function used, we splitted the load into two namely the sheddable load P2, and shiftable load P3.

Table 1
Average power consumption for non-sheddable residential loads.

Time of the day (h)	Power consumption (W)	Time of the day (h)	Power consumption (W)
1	1725	13	1885
2	1725	14	1885
3	1725	15	1885
4	1725	16	4185
5	1725	17	1985
6	1725	18	3710
7	5585	19	3860
8	1885	20	3310
9	1885	21	2300
10	1885	22	2385
11	4460	23	3385
12	2110	24	2385

The initial load and the optimized load are respectively given as:

$$d_{oc}(t) = d_{oc}^{P2}(t) + d_{oc}^{P3}(t) \tag{11}$$

and

$$d_c(t) = d_c^{P2}(t) + d_c^{P3}(t) \tag{12}$$

For the purpose of our study, the consumers initial load $d_{0c}(t)$ is taken as the sheddable and shiftable electricity consumption put together. The rand $(1,1)$ operator was also applied to the initial load to randomize the input data. This was done to ensure catering for uncertainties. Consumers optimized load $d_c(t)$ is calculated by putting the sheddable and shiftable electricity consumption put together.

2.4. Credit function

The credit incentive function we used in the study is as follows:

$$Credit_c(t) = \phi[d_{oc}(t) - d_c(t)]\left[\sum_{c=1}^{n} d_c(t) - \frac{1}{24}\sum_{c=1}^{n}\sum_{t=1}^{24} d_{oc}(t)\right] \tag{13}$$

ϕ is the indicator that determines whether a customer is eligible for credit or not and takes on values 0 and 1. At peaks, it is 1 a when customer's load is above the daily average load even after shedding and shifting load, and it is 0 when the customer's load is below the daily average load after shedding and shifting load. Similarly, for off-peaks, it is 1 when the customer's load is increased not beyond the daily average load, and it is 0 when the customer's load is above the daily average load after increasing sheddable and shiftable load. The daily average load for all customers is $\overline{D}$ which is the quantity to the right of the subtraction sign in the bigger rectangular brackets. This is the threshold about which consumers' loads is expected to fluctuate about, not going too high as in the initial peak demands and not falling too low as in the initial off-peak demand. These conditions will enable generators and distributors operate at convenient and efficient operational levels which is sustainable and environmentally friendly. They can also have good returns on their investment and also carry regular maintenance checks on their generating plants and distribution systems without interrupting the supply of electricity to consumers at any time. Global and international standards for generating clean power and energy which friendly can be achieved.

$$\Delta p_c(t) = \begin{cases} \frac{|Credit_c(t)|}{\sum_{c=1}^{N} Credit_c(t)} \cdot A_1 \cdot \frac{\sum_{c=1}^{N} d_{oc}(t) - \overline{D}}{\sum_{t=1}^{24} \tau_1(\sum_{c=1}^{N} d_{oc}(t) - \overline{D})} / d_c(t), & \sum_{c=1}^{N} d_{oc}(t) \geqslant \overline{D}, \\ \frac{|Credit_c(t)|}{\sum_{c=1}^{N} Credit_c(t)} \cdot A_2 \cdot \frac{\overline{D} - \sum_{c=1}^{N} d_{oc}(t)}{\sum_{t=1}^{24} \tau_2(\overline{D} - \sum_{c=1}^{N} d_{oc}(t))} / d_c(t), & \sum_{c=1}^{N} d_{oc}(t) < \overline{D}. \end{cases} \tag{14}$$

$A = A_1 + A_2, \tau_1, \tau_2 \in \{1,2,3,...,24\}$.

Table 2
Sheddable residential loads and their average power consumption.

Time of the day (h)	Sheddable residential loads (W)	Power consumption (W)
1	Electric equipment up to 200 W	200
2	Electric equipment up to 200 W	200
3	Electric equipment up to 200 W	200
4	Electric equipment up to 200 W	200
5	Electric equipment up to 200 W	200
6	Electric equipment up to 200 W	200
7	Fans, air conditioners and other electric equipment up to 1000 W	1300
8	Fans, air conditioners, computers, and other electric equipment up to 1000 W	1550
9	Fans, air conditioners, computers, and other electric equipment up to 1000 W	1550
10	Fans, air conditioners, computers, and other electric equipment up to 1000 W	1550
11	Fans, air conditioners, computers, and other electric equipment up to 1000 W	1550
12	Fans, air conditioners, computers, and other electric equipment up to 1000 W	1550
13	Fans, air conditioners, computers, and other electric equipment up to 1000 W	1550
14	Fans, air conditioners, computers, hairdryer, coolers, extractor hoods, and other electric equipment up to 1000 W	1550
15	Fans, air conditioners, computers, and other electric equipment up to 1000 W	1550
16	Fans, air conditioners, computers, and other electric equipment up to 1000 W	1550
17	Fans, air conditioners, computers, and other electric equipment up to 1000 W	1550
18	Fans, air conditioners, computers, and other electric equipment up to 1000 W	1550
19	Fans, air conditioners, computers, and other electric equipment up to 1000 W	1550
20	Fans, air conditioners, computers, and other electric equipment up to 1000 W	1550
21	Fans, air conditioners, computers, and other electric equipment up to 1000 W	1550
22	Fans, air conditioners, computers, and other electric equipment up to 1000 W	1550
23	Fans, air conditioners, computers, and other electric equipment up to 1000 W	1300
24	Fans, air conditioners, computers, and other electric equipment up to 1000 W	1300

Table 3
Shiftable residential loads and their average power consumption.

Shiftable residential loads	Power consumption (W)
Vacuum cleaners	1200
Washing machines	2500
Dryers	1800
Dishwashers	2000
Meat grinders	1000
Irons	1000
Total	8500 9500

where A is the total discount given to consumers by policy implementer and is predetermined. A_1 is the discount for peaks and A_2 is the discount for off-peaks. Every consumer's portion of the discount during peaks and off-peaks are proportionate to the consumer's credit obtained. This credit is given to the consumer when the consumer sheds or shifts load at peaks and increase load at off-peaks. The credit function built here considers consumers' sheddable and shiftable load cut at peaks and consumers' increase of their sheddable and shiftable load at off-peaks. The peak times are designated as τ_1 and the off-peak times are designated as τ_2. Each consumer per the amount of load shed at peaks through sheddable load and shiftable load attracts some credit incentive. Similarly, at off-peaks each consumer attracts some credit incentive for increasing load. This is done by increasing sheddable load and or shiftable. With the two periods, each consumer's credit incentive can be determined at every time t and the corresponding price change at every time t attained by the consumer can equally be computed [27]. The price change $\Delta p_c(t)$ that a customer c gets, is computed from taking the absolute form of the credit which the customer attains for shaving load at peaks and increasing load at off-peaks. Calculating the price change for a customer, if the load $d_{0c}(t)$ is above the average load for the day, then the consumer attracts a credit value whose magnitude is used in computing the price change at that peak time. This is the top part of the price change function. If a customer's load at peak time is below the average load $\overline{D}$, then the customer gets zero credit and therefore, no price change. Similarly, for off-peaks, customers are encouraged to increase their load to attract credit. The lower part of the price change function is used to compute the customer's price change at off-peaks.

The price change is based on customer load cut at peak time t to get a new price which makes the consumer happy and satisfies the consumer for the effort made in voluntarily engaging in the scheme. It is computed as follows:

$$P_c(t) = P_{0p}(t) - \Delta p_c(t) \tag{15}$$

where P_{0p}(t) is the initial price, for example critical peak price and P_c(t) is the new price the customer gets from the credit incentive. Δp_c(t) is the value that indicates change in price for customer c at time t.

3. Operational optimization and simulation results

The electricity consumption or loads were apportioned into three parts namely non-sheddable load, sheddable load and shiftable load [15]. TThat means for each consumer's demand of electricity, a part is non-sheddable, another part is sheddable and the last part shiftable. We considered then non-sheddable load to be fixed consumption for all customers and therefore needs no adjustment because it is assumed to be the basic load for essentials in life. Our optimization is focused on sheddable load and shiftable load which can be adjusted by consumers to help them pay less for electricity they use.

3.1. Classification of demands

3.1.1. Non-sheddable loads

Non-sheddable loads are loads that are basic to the consumer and they cannot do without. They consume them constantly from time to time in a day and does not change unless emergency situations or critical states. Non-sheddable loads comprise the use of household appliances such as refrigerators, coolers, aquariums, cell phones, TV, toaster, blender, electric samovar, coffee maker, microwave, electric mixer, and extractor hoods. Electricity Distributors supply various households with the minimum power of high quality that they need to use these appliances without interruption. For our study we adopted the categorized non-sheddable loads in Table 1 [15] for our residential consumption.

3.1.2. Sheddable loads

Sheddable loads are loads that the consumer can reduce or forgo in the hours of the day. These adjustments can be initiated by the consumer or even electricity distribution companies, and causes no

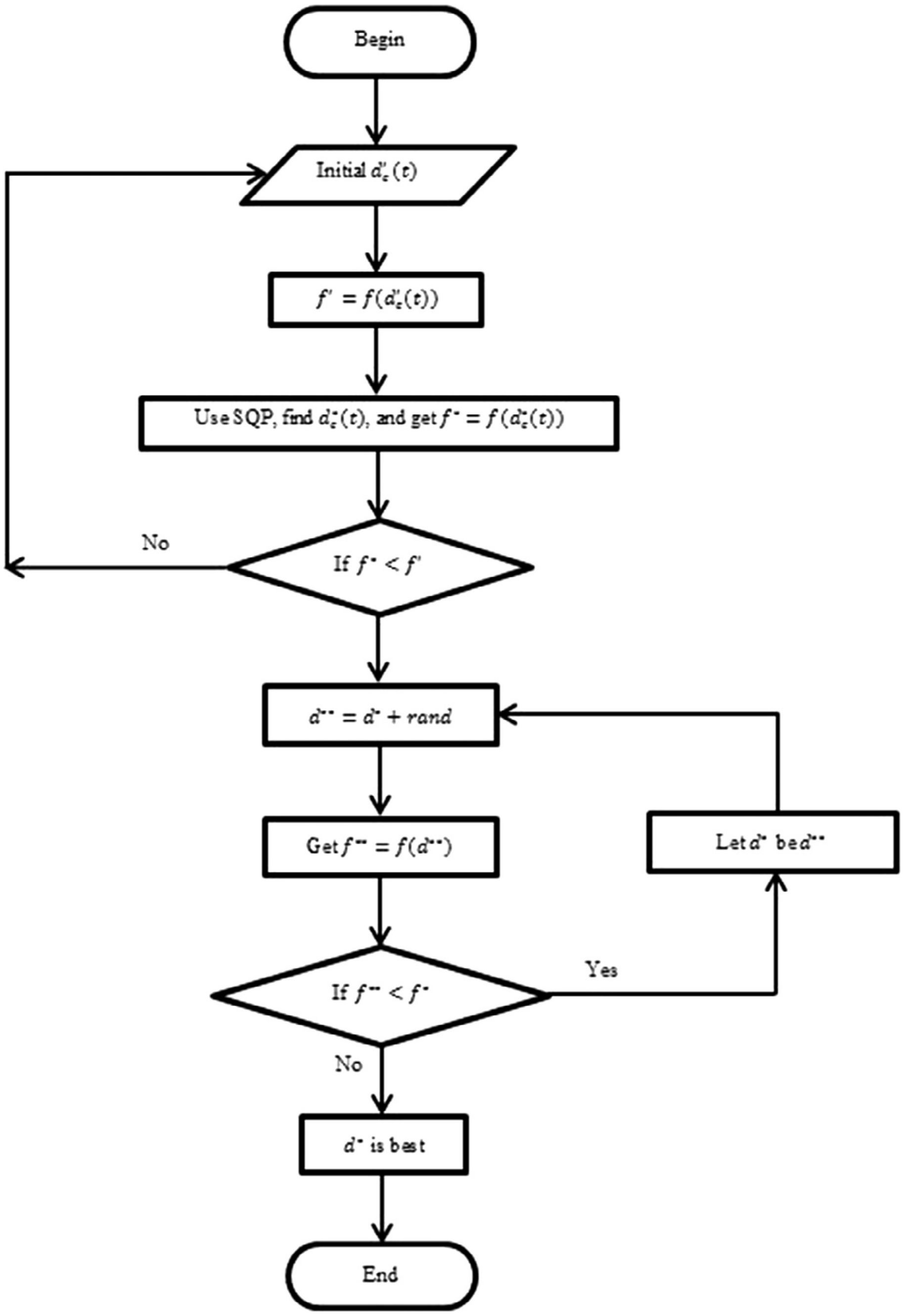
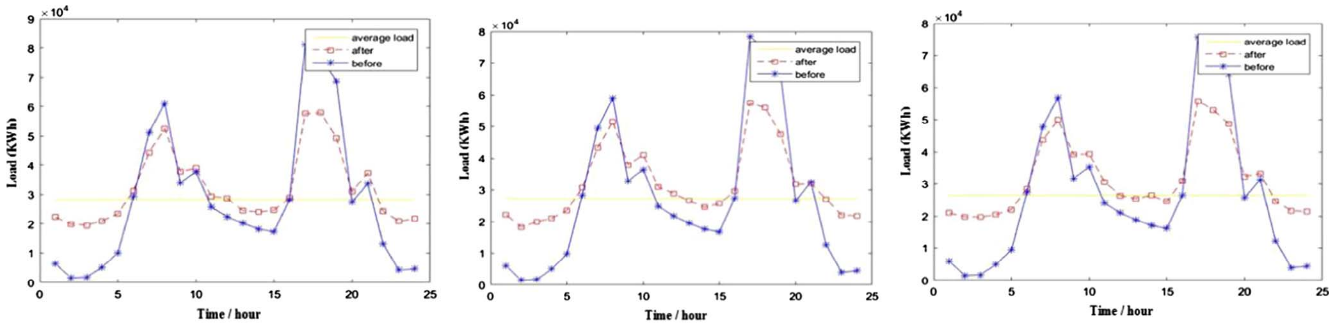


Fig. 1. Flow chart for sequence quadratic programming (SQP) method.



(a) (b) (c)

Fig. 2. Optimized consumption load curve and initial consumption load curve for case 1, case 2 and case 3. $\alpha = 10, \beta = 0.2$.

Table 4
Total sheddable load.

Time	Initial (d0P2)	Case 1 (dP2)	Case 2 (dP2)	Case 3 (dP2)
1	140	6385.52	6528.88	5310.31
2	175	6825.07	4583.96	6094.96
3	185	4096.36	6027.46	5761.29
4	218	4956.16	7284.18	6744.20
5	280	4966.02	7866.90	6412.75
6	340	5424.50	6991.48	4794.89
7	4180	6804.18	8708.07	9160.86
8	5425	8755.86	12377.20	10813.87
9	6264	7131.93	10343.96	11600.71
10	6660	9790.20	13785.35	12096.71
11	7328	11052.10	9938.76	9663.81
12	14,008	8386.03	12714.31	10117.57
13	13,910	12136.33	11719.98	10575.70
14	12,935	10283.12	10301.10	12103.38
15	12,976	8497.75	12027.86	10872.25
16	12,994	11214.18	11120.93	12475.62
17	14,251	9460.69	12560.06	10911.19
18	14,399	11160.25	14256.93	11381.39
19	14,677	10107.07	11497.03	12643.37
20	14,442	10056.32	13642.14	14189.28
21	14,357	12995.90	10918.15	12183.82
22	3394	7559.75	10469.63	7964.85
23	2252	7912.30	8015.74	7623.81
24	1629	6603.49	7179.90	6757.57

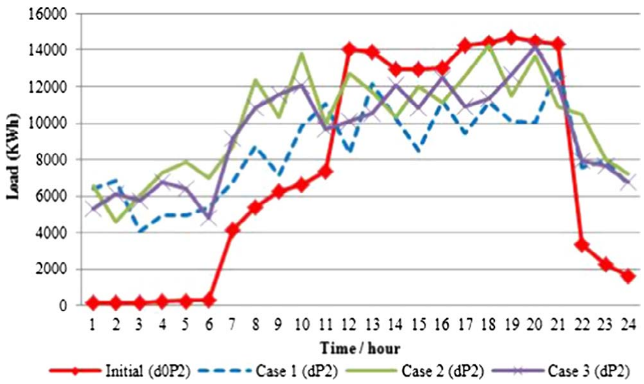


Fig. 3. Case distribution of optimized sheddable load compared with the initial.

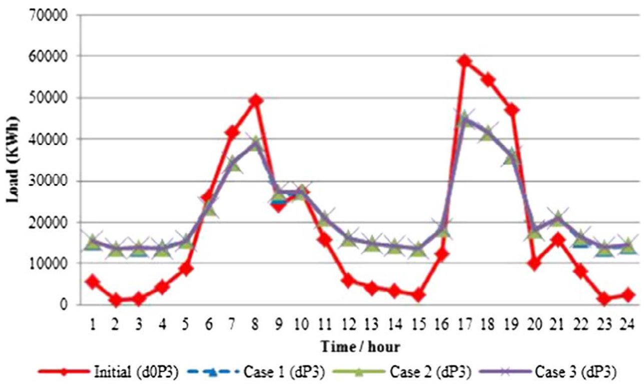


Fig. 4. Case distribution of optimized shiftable load compared with the initial.

disruption to quality of life of the consumer with regards to their well-being and security at home. It does not result in occurrences that are irreparable in the home. This is of high benefit to the customer and the power company. Our research work is focused on residential sheddable load consumption, we used the data outlined in Table 2 for that [15].

3.1.3. Shiftable loads

Shiftable loads are load consumptions during 24 h a day which a customer can use but is able to defer its time of use within the day. The shiftable loads are also of interest in our study in addition to the sheddable loads. Our target is to optimize consumers' load by considering only their sheddable and shiftable load. We used the data provided in Table 3 of [15], as residential shiftable loads to enable us establish constraints needed for our optimization (see Table 3, Fig. 1).

Table 5
Total shiftable load.

Time	Initial (d0P3)	Case 1 (dP3)	Case 2 (dP3)	Case 3 (dP3)
1	5578	15285.86	15662.46	15656.65
2	1220	13594.76	13710.22	13692.26
3	1421	13691.33	13907.07	13896.53
4	4495	13859.75	13741.75	13727.93
5	8767	15494.03	15623.20	15617.26
6	25,970	23428.50	23672.27	23656.16
7	41,781	34300.03	34490.39	34474.08
8	49,427	39261.31	39130.22	39111.80
9	24,296	26523.02	27483.67	27471.26
10	27,234	27420.71	27289.51	27271.50
11	15,738	20841.65	20960.31	20943.95
12	6158	16053.58	16236.29	16219.98
13	4254	14975.32	14844.64	14826.56
14	3451	14358.58	14227.95	14267.84
15	2658	13749.67	13632.65	13643.71
16	12,427	18650.43	18519.72	18501.50
17	58,720	45097.47	44966.16	44948.14
18	54,412	41788.97	41657.82	41639.49
19	47,071	36150.97	36019.98	36001.68
20	10,246	18276.49	18145.54	18127.43
21	15,861	20936.33	21055.94	21039.63
22	8360	16023.89	16602.67	16590.00
23	1525	13741.23	14015.31	14005.58
24	2555	14235.75	14659.13	14647.29

Table 6
Total hourly revenue.

Time	Initial Rev(0)	Case 1 Rev(t)	Case 2 Rev(t)	Case 3 Rev(t)
1	2048.76	5942.44	6144.71	5750.16
2	499.83	5144.13	4524.08	4993.42
3	575.43	4496.92	5058.16	4971.07
4	1688.67	5070.39	5679.34	5501.90
5	3241.54	6064.55	6875.73	6396.35
6	9426.87	10276.55	10895.91	10106.53
7	16467.83	12050.10	12815.60	12955.65
8	30623.87	20698.23	22950.15	22199.37
9	17061.65	18300.66	20310.21	20986.87
10	18923.02	22460.73	21516.36	20604.50
11	12877.75	17520.74	16918.39	16757.73
12	11258.68	13087.73	15457.08	14037.59
13	10140.96	14004.60	13907.55	13282.74
14	9148.30	12601.73	12598.61	13579.52
15	8728.46	11381.51	13107.85	12500.84
16	14192.54	16670.59	16543.08	17289.07
17	40739.71	20612.09	21917.21	21211.96
18	38417.18	20557.16	22109.41	20850.76
19	34473.91	19060.02	19772.07	20285.36
20	13783.31	15728.56	17637.85	17932.05
21	16870.71	18271.69	17175.69	17856.29
22	4211.46	7259.64	8323.68	7484.70
23	1353.30	5779.15	5916.02	5788.01
24	1499.13	5629.15	5891.81	5753.11

4. Discussion of results

We used fmincon in Matlab for the simulation results. Our constrained non-linear programming (CNLP) model was coded following the sequence quadratic programming (SQP) flowchart. We established three cases assigned weight (λ) to them indicating number of end-users to participate in the program. The values of the weights are 0.4, 0.8, 1.0

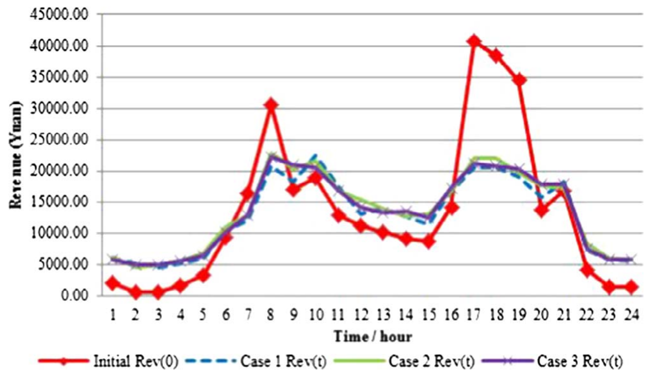


Fig. 5. Case distribution of utility cost to customer after optimization compared with the initial.

Table 7
Total hourly load.

Time	Initial d0ct	Case 1 dct	Case 2 dct	Case 3 dct
1	5718	21671.39	22191.35	20966.96
2	1395	20419.83	18294.18	19787.23
3	1606	17787.69	19934.52	19657.82
4	4713	18815.91	21025.92	20472.13
5	9047	20460.05	23490.10	22030.01
6	26,310	28853.00	30663.75	28451.05
7	45,961	41104.21	43198.46	43634.93
8	54,852	48017.18	51507.41	49925.67
9	30,560	33654.96	37827.63	39071.97
10	33,894	37210.92	41074.85	39368.21
11	23,066	31893.76	30899.06	30607.75
12	20,166	24439.61	28950.60	26337.56
13	18,164	27111.65	26564.62	25402.27
14	16,386	24641.70	24529.05	26371.22
15	15,634	22247.42	25660.52	24515.96
16	25,421	29864.61	29640.65	30977.11
17	72,971	54558.16	57526.21	55859.33
18	68,811	52949.22	55914.75	53020.87
19	61,748	46258.04	47517.01	48645.05
20	24,688	28332.80	31787.68	32316.71
21	30,218	33932.23	31974.08	33223.45
22	11,754	23583.65	27072.30	24554.86
23	3777	21653.53	22031.06	21629.38
24	4184	20839.24	21839.03	21404.86

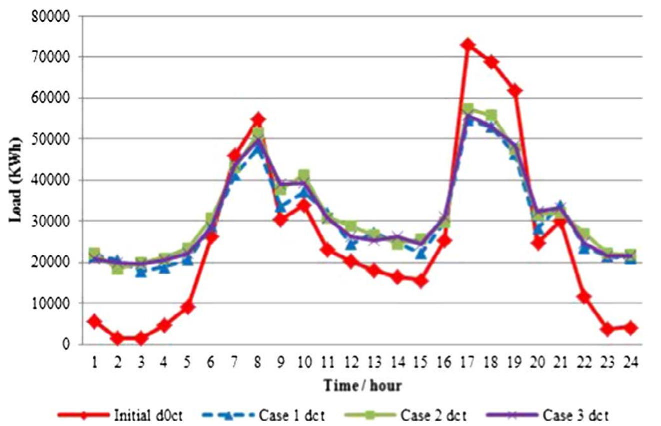


Fig. 6. Case distribution of optimal load compared with the initial.

indicating case 1, case 2, and case 3 respectively. From our simulation, the following results were obtained Fig. 2(a)–(c).

For convenience, the α-value which is amplitude of the utility function was set to 10 since we wanted a starting point which was workable. The value of β was also set to 0.2 for the reason that, we wanted the consumers' rate of approaching satisfactorily level to be in

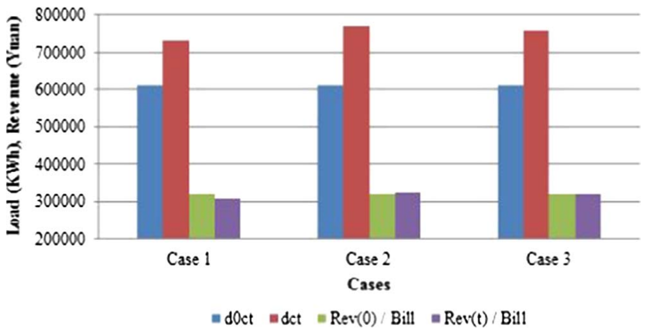


Fig. 7. Scenario distribution of optimal load and customer bill.

Table 8
Total consumer load and bill before and after optimization.

Weights	Cases	d0ct	dct	Rev(0)/Bill	Rev(t)/Bill
0.4	Case 1	611044.00	730300.73	318252.87	308669.08
0.8	Case 2	611044.00	771114.81	318252.87	324046.56
1.0	Case 3	611044.00	758232.36	318252.87	319075.59

gradual phases. From the optimal solution of the objective function, we obtained Fig. 2(a)–(c). It showed that sheddable and shiftable load can be optimized to enable consumer to cut down load at peaks and increase load at off-peaks to enjoy credit incentives that goes with it. This suggest that a combination of sheddable and shiftable load regulated by consumers between hour 6 of the day and the hour 21 of the day by shedding load at the peaks and increasing load in the trough. From the optimal patterns in Fig. 2(a)–(c), consumers can increase their loads in all the periods beforehour 6 of the day and also after hour 21 of the day to obtain credit since those periods are conducive for load increase on the grid which will not endanger its stability.

Our results show that, regulating sheddable and shiftable load of the end-user by our model reduces the residential end-user's demand in all the cases we examined. Therefore, designers and programmers of thermostatic and non-thermostatic household appliances are to consider more in their design and applications to come out with programmable appliances to function or carry out its duty during off-peaks with little or no human intervention. Our simulation results suggests that, it is best for consumers to have household appliances which operate with little or no human interaction or intervention and are in the category of shiftable load to be used overnight. That is to say that, they can be set to operate on their own while consumers retire to enjoy their night sleep since these appliances when they are through with their operation will shut down automatically by themselves or be in a standby mode. This will help consumers enjoy credit incentive by shifting load from peaks to off-peaks.

This will be convenient for power generators, distributors and retailers since generating plant need not be run at the high production cost. This ensures generating plants longevity and guarantees continuous and efficient supply of power to consumers. Efficient maintenance of generating capacity can be carried out regularly to ensure efficient and uninterrupted power supply to consumers. The release of harmful emissions into the atmosphere as a result conventional methods of producing power can be reduced to controllable level which would not be injurious to the environment and life. Other forms of generating power which are environmentally friendly (renewable energy systems) such as wind, solar, and storage such as electric vehicles could then be employed at peaks by residential end-users to augment electricity generation and load from the central grid system as indicated by recent studies.

Table 4 and Fig. 3 display the distribution of the optimal sheddable load for all the cases and the initial sheddable load as well. Case 1 was seen to shed the most load at peak whereas case 2 was observed to be the best at increasing load at off-peak. The study suggests that, sheddable loads are best used before hour 11 and also after hour 21 of the day.

The optimal results for the shiftable load for case 1, case 2, and case 3 were similar as shown in Fig. 4 and Table 5. All 3 cases showed almost the same amount of load shifts at peaks. Similarly, they all showed about equal increase in load at off-peaks. They all indicate that, shiftable loads are best used before hour 6, between hour 10 and hour 16, and also after hour 20 if end-users want to avoid high tariffs. Designers and programmers of household appliances are to research more into designing programmable appliances in the category of shiftable load which can be programmed to function or carry out its duty during off-peaks with little or without human intervention.

We compared the optimized total bill patterns on hourly basis for the 3 cases as displayed in Table 6 and realized that, case 1 had the best result of lowering cost as well as increasing load of end-user and can also be seen from Figs. 5 and 7. Here, the bills are also considered as the revenue mobilized by the power provider from the sale of power. From our simulation results, it was realized that, case 1 showed a little decrease in revenue whereas case 2 saw an increase, with case 3 also showing a marginal increase almost close to parity with the initial revenue. These deviations of the revenue cases from the initial revenue were not sharp compared to the load increases as show in Fig. 7.

From Table 7, the highest increases of load was seen in the pattern of case 2, followed by case 3 and lastly case 1 and this can also been seen in Figs. 6 and 7. In all the 3 cases, there was an increase of load, which partly demonstrates the realization our objective, that is to help end-users find the best options to increase their load and cutting down on cost without endangering the grid system.

The 3 cases are all important and can be adopted based on the policy been implemented as shown in Fig. 7 and Table 8. For the purpose and objective of our study, case 1 is be the best option since end-users are encouraged to shed and shift load at peaks and increase load at off-peaks with the expectation of having reduced bills which is met. This achieves the goal of the objective function which we proposed. It is therefore important to encourage government to give power providers corporate incentives such as tax reliefs, tax holidays etc., to assist them in rolling out such incentive-based DR programs since the cost of providing these incentive is relatively cheaper than the total cost of fixing damaged power plants, installing new conventional power plants, harmful emissions into the atmosphere and effect on life.

Case 2 and case 3 are equally good and can be used when considering power providers' interest alongside the target of ensuring that, end-users are not impoverished for load increase. From the power retailer's point of view, case 2 is preferable to case 3, since it shows marginal improvement in their revenue in Fig. 7. Therefore, one cannot solely stick a particular as the best but considering the prevailing conditions and the objective at hand can adopt the most convenient option.

5. Conclusion and policy implication

In this study, a CNLP model is proposed. The model uses a credit function to enable residential end-users to significantly shed and shift load at peaks and also increase load at off-peaks and rewards them. These were noticeable in consumers sheddable load and shiftable load cuts and adjustments at peaks and also increase of these loads at the troughs which are off-peaks. This achieves the aim of our objective function which is to seek an optimal solution that maximizes consumers satisfaction and happiness. This was not done to let consumers merely cut down on their electricity consumption at peaks, but redirect to times or periods which gives them incentives to avoid high utility cost.

Generators and distributors should not see this as a disincentive to them, since consumers are also encouraged to increase their load at the troughs. This augments for their cut down in load at peaks. This goes a long way to help generators and distributors to also maintain their generating capacities and systems for distribution. Therefore policy makers and implementers in the electricity market can adopt this model which is all inclusive and brings satisfaction to all stakeholders in the electricity market. Consumers by the result of our study are encouraged the more to increase their load at off-peaks which are affordable to enjoy more electricity at a time which is conducive for generators and distributors to operate efficiently and is congenial to the atmosphere.

This is sustainable and enables electricity producers and distributors to supply power in an environmentally friendly manner. The issue of peak shaving of load is still a challenge for manufacturing companies of household appliances to come up with modern appliances that are automated and can function independently and automatically with little or no human interaction or interference to help in the shed and shift of load at peaks. This will help regulate consumers electricity demands around grid operational levels which can be efficiently handled by generators and distributors of electricity. The environment eventually will be protected from harmful emissions which results from more conventional methods of power generation to meet high demand at peaks. The target of engaging in clean energy generation can be achieved globally if the scheme is to be adopted by policy formulators and implementers.

Future work to be undertaken is to use a multi-objective no-linear optimization programming to look into the revenue of power providers or retailers. In addition we would also want to research into optimizing the parameters in our utility function in relation to the focus of our objective function. We also intend to apply known optimization algorithms such as genetic algorithm in our future study to find out if results compare with what we have arrived at in this study or even get a better result.

Acknowledgments

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