Optimization of Energy Expenditure in Smart Homes under Time-of-Use Pricing

Omowunmi Mary Longe, Khmaies Ouahada, Suvendi Rimer and Hendrik C. Ferreira
Electrical & Electronics Engineering Science,
University of Johannesburg,
Johannesburg, South Africa.
wunmigrace@yahoo.com, {kouahada, suvendic, hcferreira}@uj.ac.za

***Abstract*–Growing peak demand has necessitated the introduction of Time-of-Use (TOU) pricing to Demand Side Management (DSM) in order to cause some peak demand to be shifted from peak to off-peak periods. Therefore, in this work, a Daily Maximum Energy Scheduling (DMES) - DSM technique is proposed. The DMES-DSM device is proposed to be installed into consumers' smart meters and schedule energy consumption for smart appliances. The DMES–DSM technique was verified with real household data and shown to be capable of optimizing households' monthly energy expenditure below approved national energy expenditure threshold and also offer Peak Demand Reduction (PDR). It offered the household considered an average monthly financial savings of 22.44% and 36.73% in summer and winter respectively on electricity bills. Utility can also benefit from the PDR for grid stability and sustainability. Also, the optimized consumption pattern differs only slightly from initial consumption pattern for enhanced consumer satisfaction.**

***Index Terms*--Daily Maximum Energy Scheduling (DMES), Demand Side Management (DSM), Household income, Smart appliances, Time-of-Use (TOU).**

I. Introduction

The transformation of the present grid to a smart grid has necessitated diverse energy management studies on the demand side for economic, environmental, infrastructural and social benefits. In the future grid, DSM technologies shall be consumer-driven, utility-driven and environment-driven. These technologies would apply energy efficiency and saving technologies, energy tariffs and pricing, distributed energy resources, incentives, energy storage, government policies and active consumer participations.

Classifying DSM techniques based on modification of consumers' load profiles offers six basic techniques [1], which include load shifting, peak clipping, conservation, load building, valley filling and flexible load. DSM techniques are often actualized through time-based or incentive-based DSM programs. Time-based DSM programs include Flat Rate Pricing (FRP), Time of Use (TOU), Real Time Pricing (RTP) and Critical Peak Pricing (CPP), while incentive-based DSM programs include Direct Load Control (DLC), Interruptible/Curtailable Services (ICS), Power Tariffs (PT) and Locational Marginal Price (LMP) [2]. TOU-based programs set electricity prices (tariffs) based on time of the day and season of the year that the energy is consumed. Hence, the higher a consumer's peak demand, the higher its energy expenditure (or electricity bill) would be.

There are many DSM optimization algorithms and techniques in literature for reduction in energy consumption cost [3]-[7], Peak Demand Reduction (PDR) [3]-[5] and also Peak-to-Average Ratio (PAR) [4]. In [3], [5], [6], the authors investigated selected household appliances, but the household energy expenditure is dependent on total consumption cost of all appliances in usage in the home. In [5], the authors proposed a framework that carries out a trade-off between minimizing household electricity payment and minimizing waiting time for the operation of appliances under RTP scheme, but appliance waiting time may not be a sufficient trade-off for household energy cost. Also, literature [7] used a repeated energy scheduling game to minimize energy consumption cost for self-interested and foresighted consumers. Then, the utility uses consumers' consumption history to determine which consumer can use energy in the future during peak time at a lower price. However, it is not certain the benefit to the utility when there are many households to be compensated with low price at peak time. Despite the works that abound in literature on DSM, none had investigated optimizing household energy consumption cost below approved energy expenditure threshold for TOU consumers, as far as the authors are concerned. Hence, the proposed algorithm in this work would produce more energy-rich households in the community and world at large.

Household energy expenditure is one of the indicators of energy poverty globally and each nation sets its energy expenditure threshold. A nation's energy expenditure threshold is chosen as from 10% to 15% of household income globally [8], [9]. Therefore, any household in a nation that spends above the approved nation's energy expenditure threshold is considered to be energy-poor [8], [10]. In developed [9], [11], [12] and developing countries [10], [13], the population that usually spends above the nation's energy expenditure threshold is mostly found among the low and middle income earners.

For instance, in South Africa, the Department of Energy (DoE) had approved 10% of household income as energy expenditure threshold [10]. According to the DoE, low-income, middle-income and high-income households in South

This work is supported in part by the National Research Foundation, South Africa (UID 85884) and Eskom Tertiary Education Support Programme (TESP) reference number 264030.

Africa spend an average of 27%, 13% and 6% of their income on energy expenditure respectively. Table I [10] presents information on income and energy expenditure by South Africa households.

TABLE I. HOUSEHOLD INCOME AND ENERGY EXPENDITURE

Quintiles	Income	% Average energy expenditure	% of population spending more than 10% of income on energy expenditure
Upper quintile	R57,000 and above	6%	13%
4th quintile	R21,003 – R57,099	11%	38%
3rd quintile	R9,887 – R21,002	14%	51%
2nd quintile	R4,544 - R9,886	17%	65%
Lower quintile	R4,543 and below	27%	74%

In this work, a TOU-based and income-based Daily Maximum Energy Scheduling (DMES) technique is proposed for residential consumers. Therefore, a DMES-DSM problem is formulated using Mixed Integer Linear Programming (MILP) [14]. MILP has been used in [15], [16] to demonstrate different DSM algorithms. A low-income South African real household data was used to validate the algorithm. This study has shown that the DMES-DSM algorithm can offer Peak Demand Reduction (PDR), PAR reduction reduced energy expenditure below the nation's energy expenditure threshold, financial and network planning for utilities, enhanced financial savings and planning for consumers.

The rest of this work is organized as follows. Energy demand and TOU tariff system in South Africa is presented in Section II. The proposed DMES-DSM device for optimized energy expenditure for TOU consumers is presented in Section III. Section IV contains the simulation results and discussions while and Section V has the conclusion.

II. RESIDENTIAL ENERGY DEMAND AND TIME-OF-USE TARIFF SYSTEM IN SOUTH AFRICA

Residential demand is characterized by two daily peak periods – the morning peak and evening peak. If peak demand growth becomes unbearable to utilities, load shedding, blackouts and/or acquiring of higher peaker plants may result. Therefore, utilities introduce TOU tariff to force some of consumers' peak demand to be shifted from peak to off-peak periods. In TOU tariff system, peak period tariffs are higher than non-peak period tariffs and winter tariffs are higher than summer tariffs for each period. Approved TOU tariffs are usually communicated to customers in advance.

The TOU tariff structure in South Africa as defined by the national utility provider, divides the year into two major seasons – winter (June to August) and summer (September to May) [17], although this is different from the weather classification in South Africa where there is autumn, winter, spring and summer [18].

In the newly approved TOU structural adjustment by the National Energy Regulator of South Africa (NERSA), TOU periods are changing from 07:00 - 10:00 hrs to 06:00 – 09:00 hrs for morning peak, and from 18:00 – 20:00 hrs to 17:00 – 19:00 hrs for evening peak during winter months effective from March 2015 [19]. However, summer TOU periods remain 07:00 - 10:00 hrs and 18:00 – 20:00 hrs for morning and evening peak periods respectively. This change may lead to some inconveniences for consumers since the average wake-up time in South Africa is 06:24 hrs [20]. However, the proposed DMES-DSM solution ensures affordable energy expenditure for households throughout the year.

III. DMES-DSM FOR ENHANCED DEMAND SIDE MANAGEMENT IN SMART HOMES

Household energy expenditure is the cumulative cost of energy consumed by all appliances in the household within a period of time. The monthly household energy expenditure shall be optimized in this work by optimizing from the hourly and daily energy expenditure levels. The energy consumption by smart home appliances connected in a smart home to a smart meter is studied to ensure that household energy expenditure is less than the approved energy expenditure threshold according to the household income irrespective of the season and TOU tariff implemented.

A. Smart Home DMES-DSM System Description

The DMES-DSM technique shall require a smart home with smart appliances connected to the smart meter as is envisaged in a smart grid. The DMES-DSM device is proposed to be installed into the smart meter and the proposed DMES-DSM system model is shown in Fig. 1.

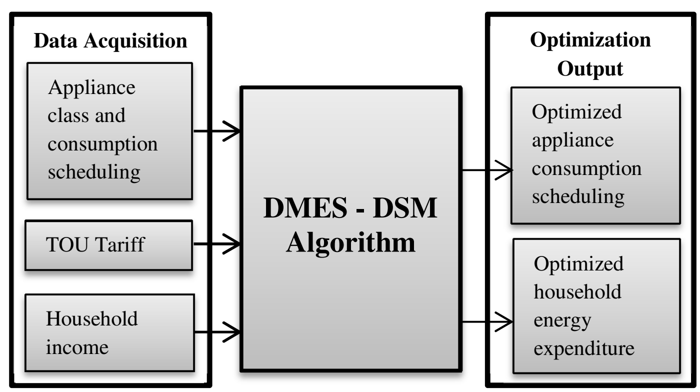

Figure 1. The DMES-DSM System Model

The smart appliances in the home are classified into class A and class B categories. Class A smart appliances are the smart appliances whose energy consumption takes priority in the smart home and are most essential for the comfort of the consumer according to the consumer's preferences e.g. lighting bulbs, electric stove, phone charger etc. On the other hand, class B smart appliances are those smart appliances whose consumption in the smart home can be shifted to later times in the day or switched off in order for the household not to exceed certain hourly and daily energy consumption limit e.g. room heater, water heater etc. However, some appliances can possess dynamic classification between class A and B based on consumer's preferences or priorities. A list of smart appliances considered are shown in Table II.

TABLE II. LIST OF HOUSEHOLD SMART APPLIANCES

Smart Appliance	Class	Appliance ID	Power rating, P (kW)
Radio	A	A_1	0.015
TV	A	A_2	0.040
Electric Stove	A	A_3	2.000
Inside Bulbs	A	A_4	0.040
Outside bulbs	A	A_5	0.040
Electric Kettle	A	A_6	1.000
Fan *	A	A_7	0.080
Microwave	A	A_8	1.000
Phone charger	A	A_9	0.010
Toaster	A	A_{10}	1.000
Refrigerator	A	A_{11}	0.250
Electric Iron	B	B_1	1.000
Room heater*	B	B_2	2.000
Water heater	B	B_3	2.500
DVD player	B	B_4	0.025

*Seasonal appliance

B. Smart Appliances Energy Scheduling Formulation

A smart appliance can be denoted by A_n for $n = 1, 2, \ldots, \bar{n}$ or B_m for $m = 1, 2, \ldots, \bar{m}$ for every A_n and B_m belonging to $\mathbb{A} = \{A_1, A_2, \ldots, A_{\bar{n}}\}$ and $\mathbb{B} = \{B_1, B_2, \ldots, B_{\bar{m}}\}$, where $\mathbb{A}$ and $\mathbb{B}$ are the sets of class A and class B smart appliances in a household respectively.

The aggregate class hourly energy consumed by all class A and B appliances is given by (1) and (2) respectively:

$$E_{A,h} = E_{A_1,h} + E_{A_2,h} + \ldots + E_{A_{\bar{n}},h} = \sum_{A_n \in \mathbb{A}} E_{A_n,h}, \quad (1)$$

$$E_{B,h} = E_{B_1,h} + E_{B_2,h} + \ldots + E_{B_{\bar{m}},h} = \sum_{B_m \in \mathbb{B}} E_{B_m,h}, \quad (2)$$

where $E_{A_n,h}$ is the energy consumed by a class A appliance and $E_{B_m,h}$ is the energy consumed by a class B appliance at a time h for $h \in \mathbb{H}$, and $\mathbb{H}$ = [1, 2, .., 24]. Therefore, a household's total instantaneous hourly energy, E'_h at every time h by all the smart appliances is expressed as (3):

$$E'_h = E_{A,h} + E_{B,h} = \sum_{A_n \in \mathbb{A}} E_{A_n,h} + \sum_{B_m \in \mathbb{B}} E_{B_m,h}. \quad (3)$$

The total daily scheduled energy consumed in the household is given by (4):

$$E_h = \sum_{h=1}^{h=24} E'_h = E_A + E_B. \quad (4)$$

For $E_A = \sum_{h \in \mathbb{H}} \sum_{A_n \in \mathbb{A}} E_{A_n,h}$ and $E_B = \sum_{h \in \mathbb{H}} \sum_{B_m \in \mathbb{B}} E_{B_m,h}$. However, energy consumption for each class appliance is $C_{A_n,h} = P_{A_n} t_{A_n,h}$, and $C_{B_m,h} = P_{B_m} t_{B_m,h}$, $where\ t \neq h\ and\ t \in \mathbb{R}$, P is the power rating of each appliance as shown in Table II and t is duration of use. The switching state of each smart appliance can be represented by a binary integer vector $\mathbf{s}$ since the smart appliances were assumed to take on either 0 or 1 switching states per time:

$$\mathbf{s} = [s_1, s_2, s_3, \ldots, s_{24}]^T, \quad s \in \{0,1\}^{24x1}. \quad (5)$$

However, consideration for appliances with multi-level states of power consumption is in future work. The hourly scheduled energy consumption is found using $E_{A_n,h} = \mathbf{C}_{A_n,h}\mathbf{s}$ and $E_{B_m,h} = \mathbf{C}_{B_m,h}\mathbf{s}$ for each class appliance, where $\mathbf{C}_{A_n,h}$ and $\mathbf{C}_{B_m,h}$ are 24-element row matrices with only one non-zero entry $C_{A_n,h}$ and $C_{B_m,h}$ respectively at column positions j=h for every entry C_{ij}.

C. Optimized Household Energy Expenditure Formulation

This work aims at optimizing household monthly energy expenditure from a daily optimization approach. Therefore, the optimized household energy expenditure Υ_{op} is expressed as a function of certain variables in (6):

$$\Upsilon_{op} = f\big(I, E_{A,h}, E_{B,h}, T, d\big), \quad (6)$$

where I is the household income, T is the tariff and d is the number of days in the month. For FRP consumers, the maximum daily allowable energy consumption E_{max_d} can be generally expressed as follows:

$$E_{max_d} \propto \frac{I}{Td}: \qquad E_{max_d} = \frac{kI}{Td}, \quad (7)$$

where k is a nation's energy expenditure threshold, which varies from 10% to 15% of household income [8], [10]. In the South African scenario used as a case study in this work, $k = 0.1$ (i.e. 10%) [10]. Therefore, (7) can be re-written for FRP South African DMES customers as (8):

$$E_{max_d} = \frac{0.1I}{Td}. \quad (8)$$

The DMES device was first proposed by the authors for FRP customers in [21]. However for TOU consumers, (7) would not hold since T is not same within 24 hours, but depends on the time of use of energy in the day and season. Monthly maximum expected energy expenditure Υ^m_{max} for each household is proposed to be less than or equal to kI (i.e. $\Upsilon^m_{max} \leq kI$), and the daily maximum expected energy expenditure Υ^d_{max} is obtained using (9):

$$\Upsilon^d_{max} = \frac{\Upsilon^m_{max}}{d}. \quad (9)$$

This is done so that the consumer does not reach Υ^m_{max} before month ends. Then, Υ^d_{max} was initially divided equally among 24 hours for mathematical simplicity and the maximum expected hourly energy expenditure Υ^h_{max} is given by (10):

$$\Upsilon^h_{max} = \frac{\Upsilon^d_{max}}{24}. \quad (10)$$

The maximum allowable energy consumption per hour E_{max_h} is therefore expressed in (11) using T_h as the hourly TOU tariff:

$$E_{max_h} = f\left(\Upsilon_{max}^{h}, T_h\right) = \frac{\Upsilon_{max}^{h}}{T_h}. \quad (11)$$

To enhance the comfort of the customers and avoid energy wastage, the DMES-DSM device is programmed such that the hourly energy saved $E'_{s_h} = E_{max_h} - E'_h$ is added to the E_{max_h} of the next hour. However, if the consumer is moving to a different tariff period (e.g. from non-peak period to peak period or vice versa), then the energy saved from the previous hour $E'_{s_{-h}}$ is added to the current hour's E_{max_h} at the rate of the TOU tariff of the current hour h using $\frac{E'_{s_{-h}}T_{-h}}{T_h}$, where T_{-h} is the previous hour TOU tariff and T_h is the current hour TOU tariff. The monthly optimized energy expenditure Υ_{op}^{m} is expressed as the summation of the daily optimized energy expenditure Υ_{op}^{d} from the first day d_1 to the last day d_l of the month in (12):

$$\Upsilon_{op}^{m} = \Upsilon_{op}^{d_1} + \Upsilon_{op}^{d_2} + \cdots + \Upsilon_{op}^{d_l} = \sum_{d_1}^{d_l} \Upsilon_{op}^{d}. \quad (12)$$

However, Υ_{op}^{d} is found in terms of the hourly optimized energy expenditure Υ_{op}^{h} in (13) and Υ_{op}^{m} now by (14):

$$\Upsilon_{op}^{d} = \Upsilon_{op}^{1} + \Upsilon_{op}^{2} + \ldots + \Upsilon_{op}^{24} = \sum_{h=1}^{24} \Upsilon_{op}^{h}. \quad (13)$$

$$\Upsilon_{op}^{m} = \sum_{d_1}^{d_l} \sum_{h=1}^{24} \Upsilon_{op}^{h}. \quad (14)$$

However, $\Upsilon_{op}^{m} \leq \Upsilon_{max}^{m}$, $\Upsilon_{op}^{h} \leq \Upsilon_{max}^{h}$, $E'_h \leq E_{max_h}$ and $E_h \leq E_{max_d}$. Therefore, the optimized hourly energy expenditure Υ_{op}^{h} is given by (15):

$$\Upsilon_{op}^{h} = E'_h T_h, \quad (15)$$

An hourly TOU tariff system is considered in this work since the utility uses hourly TOU pricing and is therefore, represented by the tariff vector matrix $\mathbf{T}$ where $\mathbf{T} = [T_1, T_2, T_3, \ldots, T_{24}]^T$ $\forall T_h \in \mathbf{T}$. Therefore, the optimized daily energy expenditure is given as (16):

$$\Upsilon_{op}^{d} = \sum_{h=1}^{h=24} \Upsilon_{op}^{h} = E'_1 T_1 + E'_2 T_2 + \cdots + E'_{24} T_{24}. \quad (16)$$

The TOU tariff for single-phase domestic customers in Johannesburg, South Africa was applied in this work as shown in Table III [22] and the TOU durations for peak, standard and off-peak periods are presented in Table IV [17].

TABLE III. TOU TARIFF FOR SINGLE-PHASE DOMESTIC CUSTOMERS

Period	**Summer (c/kWh)**	**Winter (c/kWh)**
Peak	109.89	262.09
Standard	86.93	104.65
Off-peak	68.39	73.38

TABLE IV. DURATION OF TOU PERIODS

Days of the week	**TOU Periods**		
	Peak (hrs)	***Standard (hrs)***	***Off-peak (hrs)***
Weekdays	07:00 - 10:00 18:00 - 20:00	06:00 - 07:00 10:00 - 18:00 20:00 - 22:00	00:00 - 06:00 22:00 - 24:00
Saturdays	None	07:00 - 12:00 18:00 - 20:00	00:00 - 07:00 12:00 - 18:00 20:00 - 00:00
Sundays	None	None	All day

A threshold notification is introduced so that the customer is aware of near E_{max_h} consumption per hour. The hourly threshold, $E'_{TH_h} = 0.9E_{max_h}$. At time, $h_{E'_{TH_h}}$, the DMES-DSM device begins cutting off power supply to class B appliances in order of decreasing energy consumption within the hour, but will restore the supply at the beginning of the next hour.

The 90% consumption threshold was arbitrarily chosen so that the optimized consumption pattern does not vary too much from the initial consumption pattern of the consumer so as enhance consumer satisfaction. However, any other threshold can be chosen and the effect of such tested on the algorithm.

D. DMES-DSM Optimization Problem and Algorithm

The DMES-DSM optimization problem can be formulated as a MILP problem in (17) using the branch and bound method [14] implemented in CPLEX [23]:

$$\begin{aligned}
&\min \quad \Upsilon_{op}^{m} \\
&\text{s.t.} \quad \Upsilon_{op}^{m} \leq kI, \qquad 0.1 \leq k \leq 0.15, \\
&\quad \Upsilon_{op}^{m} = \sum_{d_1}^{d_l} \sum_{h=1}^{24} \Upsilon_{op}^{h}, \ \forall h \in \mathbb{H}, \\
&\quad \Upsilon_{op}^{h} = E'_h T_h, \forall h \in \mathbb{H}, T_h \in \mathbf{T}, \\
&\quad E_{A_n,h} = \mathbf{C}_{A_n,h}\mathbf{s}, A_n \in \mathbb{A}, h \in \mathbb{H}, \\
&\quad E_{B_m,h} = \mathbf{C}_{B_m,h}\mathbf{s}, B_m \in \mathbb{B}, h \in \mathbb{H}, \\
&\quad \mathbf{s} = [s_1, s_2, s_3, \ldots, s_{24}]^T, \ s \in \{0,1\}^{24x1}, \ \forall s, \\
&\quad E'_h = \sum_{n=1, A_n \in \mathbb{A}}^{\bar{n}} E_{A_n,h} + \sum_{m=1, B_m \in \mathbb{B}}^{\bar{m}} E_{B_m,h}, \\
&\quad E_h = \sum_{h=1}^{h=24} E'_h = E_A + E_B, \\
&\quad \sum_{B_m \in \mathbb{B}} E_{B_m,h} \leftarrow 0 \ at \ h_{E'_{TH_h}} \in \mathbb{H}, E'_{TH_h} = 0.9E_{max_h}, \\
&\quad \Upsilon_{op}^{m} \leq \Upsilon_{max}^{m}, \Upsilon_{op}^{d} \leq \Upsilon_{max}^{d}, \ \Upsilon_{op}^{h} \leq \Upsilon_{max}^{h}, \\
&\quad E'_h \leq E_{max_h}, \ E_{A_n,h} \geq 0, E_{B_m,h} \geq 0, \\
&\quad E_{A_n,h} \geq 0, \ E_{B_m,h} \geq 0, \forall A_n \in \mathbb{A}, \forall B_m \in \mathbb{B}. \qquad (17)
\end{aligned}$$

The DMES-DSM algorithm is shown below.

DMES-DSM Algorithm

input: $\mathbf{C}_{A_n,h}, \mathbf{C}_{B_m,h}, \mathbf{s}, I, E_{max_h}, E_{TH_h}, \mathbf{T}$,
output: $E_h', E_h, \Upsilon_{op}^h, \Upsilon_{op}^d, \Upsilon_{op}^m$.
repeat
  if time $h \in \mathbb{H}$ **then**
   Solve (18)
   print E_h' and Υ_{op}^h
   Update E_h and Υ_{op}^d according to the solution.
    if $E_h' \leq E_{max_h}$ **then**
    Compute $E_{s_h}' = E_{max_h} - E_h'$
     if current hour has same tariff with previous hour **then**
      Current hour $E_{max_h} =$ current hour $E_{max_h} + E_{s-h}'$
      Current hour E_{max_h} and E_{TH_h}' are updated accordingly
     else Current hour $E_{max_h} =$ current hour $E_{max_h} + \frac{E_{s-h}' T_{-h}}{T_h}$
     Current hour E_{max_h} and E_{TH_h}' are updated accordingly
     end if
   else current hour E_{max_h} and E_{TH_h}' remains as given
   end if
until $h = 24{:}00hrs$
print E_h, Υ_{op}^d.
Timer resets and repeats same process next day until month ends and Υ_{op}^m is generated.

IV. RESULT AND DISCUSSION OF DMES-DSM SIMULATIONS

Numerical results of the simulated DMES-DSM algorithm are presented in this section to validate the theoretical analyses carried out. In order to test the DMES-DSM algorithm, the survey of a low-income household was conducted. The survey obtained from the household information about appliance possession, times and duration of usage both daily and seasonally, household income and electricity bills for a year. The consumption data generated from the survey were checked with the electricity bills obtained and validated. From the survey, the household informed that it earns an average monthly income of R4,000 and is comprised of two adults who leave home for work often by 07:30 hrs and return home by 17:00 hrs on Monday - Saturday.

The comparison between hourly energy consumption and hourly consumption cost under initial and DMES-DSM scenarios are shown in Figs. 2 and 3 respectively. The initial results are from the household data obtained from the survey. It can be seen from Figs. 2 and 3 that the DMES-DSM device reduced energy consumption, consumption cost and consequently kept the household energy expenditure below 10% of householder's income. Furthermore, it also yielded average 21% and 30% PDR during the morning and evening peak periods respectively. Consequently, PAR was also reduced. The aggregate of the PDR and PAR reduction over many households or consumers would offer the grid increased stability.

The summary of the result of the DMES-DSM algorithm on the households' monthly energy expenditure is presented in Table V showing the initial monthly energy expenditure $\Upsilon_{initial}^m$ without DMES-DSM device and optimized monthly energy expenditure Υ_{op}^m with the DMES-DSM device in summer and winter. The proposed DMES-DSM algorithm showed that it could help the household to spend below 10% of income on energy expenditure. The average monthly financial savings observed for the low-income household under consideration were R92.88 (22.44%) and R213.01 (36.73%) in summer and winter respectively, where R stands for Rand (South African currency).

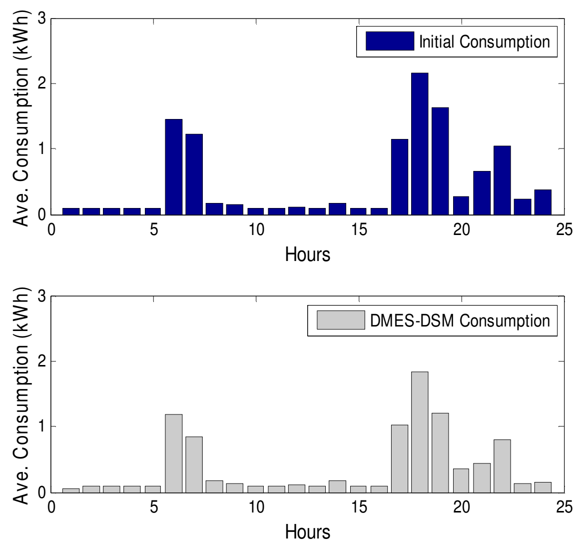

Figure 2. Average household hourly energy consumption during winter

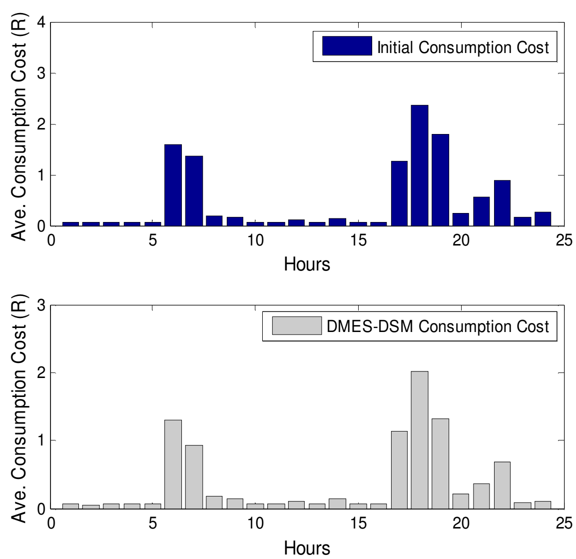

Figure 3. Average household hourly consumption cost during summer

TABLE V. COMPARISON OF HOUSEHOLD'S INITIAL AND DMES-DSM OPTIMIZED ENERGY EXPENDITURE

Income	Υ_{max}^m	**Average Summer monthly energy expenditure**		**Average Winter monthly energy expenditure**	
		$\Upsilon_{initial}^m$	Υ_{op}^m	$\Upsilon_{initial}^m$	Υ_{op}^m
R4,000	R400	R413.91	R321.03	R579.90	R366.89

R – Rand (South African currency)

Even if the constant meter charge (R12.03 for this consumer) is added to the optimized bill Υ_{op}^{m}, the total monthly energy expenditure will still be $\leq kI$.

Although, the DMES-DSM algorithm had helped the household to reduce consumption cost and peak demand, it is however, essential to determine the level to which the optimized consumption affected household initial consumption pattern. The daily average result of this variation (optimized consumption - initial consumption) was approximately 12%, which shows that the DMES-DSM technique gave the consumer about 88% energy satisfactions. The percentage satisfaction is expected to increase month after month as the consumer gets used to the device. Also, if this household would apply proposed Electricity Usage Plan (EUP) in [3] for the some class B appliances, it would be able to meet more of its energy needs within the expected budget for energy expenditure. Also, the algorithm can be extended to more appliances and households to prove its scalability and reliability.

Future work could include a dynamic energy pricing scenario, where the DMES-DSM algorithm can be modified to read tariff based on the day-head information received from the utility. The consumer's satisfaction with the DMES-DSM algorithm under various tolerance levels are presented in future work due to page constraints. Also, apart from residential consumers, commercial and industrial consumers can also subscribe to this device to optimize their consumption and energy expenditure within a budget.

V. CONCLUSION

The DMES-DSM algorithm has been used to show how household monthly energy expenditure of TOU customers can be kept below the energy expenditure threshold of their nation by scheduling hourly and daily energy consumption of smart appliances used in smart homes. This would offer benefits to all stakeholders in the energy industry including consumers, utility providers and the government. Consumers would benefit through financial savings, energy savings and enhanced financial planning for the household. The utilities' benefits could include better network planning (generation, transmission and distribution networks), reduced investment cost on peaker plants and grid stability and sustainability. The government would also benefit as more households in the nation would be spending below the energy expenditure threshold on electricity bills. Hence, there will be more energy-rich households in the nation. Therefore, this work is novel to using DSM technique for households to spend on electricity bill below approved energy expenditure threshold.

REFERENCES

[1] I.K. Maharjan, *Demand Side Management: Load Management, Load Profiling, Load Shifting, Residential and Industrial Consumer, Energy Audit, Reliability, Urban, Semi-Urban and Rural Setting,* Saarbrücken, Germany: Lambert Academic Publication (LAP), 2010.

[2] D. Steen, L.A. Tuan and L. Bertling, "Price-Based demand-side management for reducing peak demand in electrical distribution systems – with examples from Gothenburg," *in Proc. 2012 Nordic Conf. on Electricity Distribution System Management and Development,* pp. 1-11.

[3] O. M. Longe, S. Rimer, K. Ouahada, H. C. Ferreira, "Time programmable smart devices for peak demand reduction of smart homes in a microgrid," *in Proc. 2014 IEEE International Conf. on Adaptive Science and Technology*, pp. 1-6.

[4] A. Mohsenian-Rad and A. Leon-Garcia. Optimal residential load control with price prediction in real-time electricity pricing environments. *IEEE Trans on Smart Grid,* 1(2):120–133, 2010.

[5] E. Ancillotti, R. Bruno and M. Conti, "Smoothing peak demands through aggregate control of background electrical loads," *in Proc. 2014 IEEE Innovative Smart Grid Technologies (ISGT) - North America*, pp. 1-4, 2014.

[6] H.P. Khomami, M.H. Javidi, "An Efficient Home Energy Management System for Automated Residential Demand Response," *in Proc. 2013 13th International Conference on Environment and Electrical Engineering*, pp. 307-312.

[7] L. Song, Y. Xiao, and M. van der Schaar, "Demand side management in smart grids using a repeated game framework*," IEEE J. Select. Areas Commun.,* vol. 32, no. 7, pp. 1412–1424, Jul. 2014.

[8] R. Schuessler, "Energy poverty indicators: Conceptual issues, Part I: The ten-percent-rule and double median/mean indicators", Centre for European Economic Research, 2014.

[9] S. Fankhauser and S. Tepic, "Can poor consumers pay for energy and water"? European Bank for Reconstruction and Development, 2007.

[10] Department of Energy, South Africa, "A survey of energy-related behaviour and perceptions in South Africa – the residential sector", 2012.

[11] M. Mirzatuny. Energy management can empower everyone regardless of income level. Environmental Defense Fund, US Climate and Energy Program. [Online]. Available: www.blogs.edf.org. Dec. 2014.

[12] A. McAllister. Energy costs, Conservation, and the Poor. [Online]. Available: www.reimaginerpe.org/node/965.

[13] M. Auffhammer and C. D. Wolfram, "Powering up China: income distributions and residential electricity consumption," pp. 1–14, 2014.

[14] L. N. Vaserstein, *Introduction to Linear Programming*, Upper Saddle River, New Jersey: Pearson Educational Inc., 2003.

[15] S. Salinas, M Li and P. Li, "Multi-objective optimal energy consumption scheduling in smart grids," *IEEE Trans Smart Grid*, vol. 4, no. 1, pp. 341–348, 2013.

[16] Z. Zhu, J. Tang, S. Lambotharan, W. H. Chin and Z. Fan, "An integer linear programming based optimization for home demand-side management in smart grid," *in Proc. 2012 IEEE PES Innovative Smart Grid Technologies- North America*, pp. 1–5.

[17] Eskom, "Schedule of Standard Prices for Eskom Tariffs 1 April 2013 to 31 March 2014 for Non-Local Authority Supplies and 1 July 2013 to 30 June 2014 for Local Authority Supplies," [Online]. Available: www.eskom.co.za/customercare/tariffsandcharges/documentsSchedule_of_Std_Prices_2013_14_excl_Transflex1.pdf. Feb. 2013.

[18] South Africa Weather Service (SAWS), "How are the dates of the four seasons worked out," [Online]. Available: www.weathersa.co.za/learning/weather-questions/82-how-are-the-dates-of-the-four-seasons-worked-out?recache=1. Feb. 2015

[19] National Energy Regulator of South Africa (NERSA), "Eskom's 2015/16 Time of Use (TOU) Structural Adjustment," [Online]. Available: www.nersa.gov.za/eskom-tou-structural-adjustment.pdf. Dec. 2014.

[20] S. Writer, South Africans are the earliest risers in the world, BusinessTech, [Online]. Available: www.businesstech.co.za/news/international/86268/south-africans-are-the-earliest-risers-in-the-world/ May 2015.

[21] O. M. Longe, K. Ouahada, S. Rimer, H. Zhu and H. C. Ferreira, "Effective Energy Consumption Scheduling in Smart Homes," *in Proc. 2015 IEEE Africon*, pp. 1-5.

[22] City of Johannesburg, "2014/15 Approved tariffs," [Online]. Available: www.joburg.org.za/approvedtariffs/. 2015.

[23] IBM, *IBM ILOG CPLEX optimization studio – getting started with CPLEX,* version 12, release 4, United States of America: IBM Corporation, 2011.