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Distributed Demand Side Management with Battery Storage for Smart Home Energy Scheduling

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Abstract: The role of Demand Side Management (DSM) with Distributed Energy Storage (DES) has been gaining attention in recent studies due to the impact of the later on energy management in the smart grid. In this work, an Energy Scheduling and Distributed Storage (ESDS) algorithm is proposed to be installed into the smart meters of Time-of-Use (TOU) pricing consumers possessing in-home energy storage devices. Source of energy supply to the smart home appliances was optimized between the utility grid and DES device depending on energy tariff and consumer demand satisfaction information. This is to minimize consumer energy expenditure and maximize demand satisfaction simultaneously. The ESDS algorithm was found to offer consumer-friendly and utility-friendly enhancements to DSM program such as energy, financial and investment savings, reduced/eliminated consumer dissatisfaction even at peak periods, Peak-to-Average-Ratio (PAR) demand reduction, grid energy sustainability, socio-economic benefits and other associated benefits such as environmental-friendliness.

Keywords: Demand Side Management (DSM); Distributed Energy Storage (DES); Energy Scheduling and Distributed Storage (ESDS) algorithm; energy expenditure; Time-of-Use (TOU) pricing

1. Introduction

The smart grid is envisioned to offer grid reliability, sustainability, efficiency and security with better consumer participation and environmental friendliness. It will be an environment with bi-directional flow of power and information between utilities and consumers through enabling information and communication technologies [1].

… goals to be … iance energy consumption scheduling, peak demand reduction (PDR), and Peak-to-Average-Ratio (PAR) demand reduction with some level of consumer preferences.

The need to enhance power supply stability in the grid has led to exploring additional power supply sources such as Distributed Energy Resources (DERs) e.g. wind turbines and solar panels, and Distributed Energy Storage (DES) e.g. batteries, electric vehicles, and fuel cells. Energy storage in batteries for use in consumer premises is promising due to recent development in battery designs with features such as larger storage capacities, longer discharge period, and better charging and discharging efficiencies [6].

Generally, when consumers' consumption is scheduled, it is the peak period demand that is often shifted to non-peak period thereby leading to consumer dissatisfaction/discomfort. Hence, this work intends through its proposed DSM algorithm to offer PDR benefits to the utility with reduced or negligible peak period demand dissatisfaction to consumers, by optimizing energy supply and demand in consumer premises through the incorporation of in-home DES device. The proposed Energy Scheduling and Distributed Storage (ESDS) algorithm will carry out energy consumption, storage and expenditure optimization in the smart homes equipped with in-home DES device. The ESDS algorithm optimizes energy demand and supply in the home between the grid and battery depending on grid energy price and consumer preferences. The ESDS optimization problem was formulated using convex programming and can be installed into smart meters in consumers' premises distributedly.

The proposed algorithm would offer energy expenditure reduction and affordability, better consumer satisfaction even at peak period, utility savings on peaker plants, reduced PAR demand and reduced CO_2 emissions from peaker plants. Consumer's privacy is also offered, since the consumers do not need to send their energy consumption schedule to one another within the network, but to the utility only. This would in essence reduce signaling complexity and communication investment costs in the smart grid infrastructure.

The rest of the work is organized as follows. Some related literature on DES for DSM applications are presented in Section II, while a description of the ESDS model is presented in Section III. The ESDS problem formulation is in Section IV. Section V contains the simulation results and discussions while Section VI contains the conclusion of the work.

2. Related Work

Energy storage batteries can be installed into consumers' premises as standalone or grid-connected sources. Energy storage capabilities in DSM programs have been studied in some literature [2,6,8,9]. The work in [2,6] applied parallel DSM algorithms to optimize energy consumption. However, [2] included modeling of distributed generators with capacity to trade with the grid in order to reduce consumer payments for electricity and utility cost, but with a penalty if consumer's load is higher than a level compared with other consumers in the network. The work thereby constrains a consumers' satisfaction to be dependent on other consumers' consumption. In [6], the authors presented a distributed energy consumption and storage optimization algorithm to minimize consumer energy payments while allowing the consumers to update their strategies simultaneously, but without modeling consumer satisfaction and detail battery storage profile with parameters that could influence the results presented. In [8], a model for grid, distributed energy production and storage with an independent centrally controlled day-ahead optimization algorithm was proposed for consumers. However, the selfish optimization of individual consumer's consumption in such a pricing system where aggregate demand influences overall energy price may pose an unfair energy price on some consumers in the network. A large scale Energy Storage System (ESS) was proposed in [9] for centralized congestion relief in a smart grid using a real-time optimal dispatch algorithm, but it could be incapacitated by low penalty factors and imperfect forecast of energy price and congestion signals.

Although many algorithms have proposed energy consumption scheduling algorithms for DSM, but the proposed ESDS algorithm in this paper attempts to optimize consumer energy consumption and demand satisfaction simultaneously in smart homes. It further applies its dissatisfaction model according to the nature of the appliance. Mathematical optimization techniques are promising in the design of DSM programs [4-7,11] and it will be employed also in this work to model the proposed ESDS problem.

3. Description of ESDS Architecture

Each smart home considered in this work is assumed to possess an energy storage device (e.g. batteries) installed within its premise as illustrated in Figure 1. The energy scheduling information from the consumers are sent to the utility via the Data Aggregation Point (DAP), while pricing and billing information from the utility are also passed through the same channel to the consumers.

The appliances can either be powered from the grid or the battery depending on the cost of electricity at the particular time. Therefore, the model is designed such that the household uses energy primarily from the grid at low tariff periods and primarily from the batteries at high tariff periods. Furthermore, the battery is only scheduled to be charged from the grid at low price periods.

In a Time-of-Use (TOU) pricing scenario, the cost of energy consumption to the consumer is higher at peak times than non-peak times and also higher during winter than summer as shown in Table 1[12] for week days. The whole day is off-peak pricing on Sundays while Saturdays have standard pricing for 07:00-12:00 hrs and 18:00-20:00 hrs, and the rest of the day is off-peak pricing [12]. A high disparity occurs between summer and winter peak period tariffs than other period tariffs. This was intended by the utility to force reduced demand from the grid during the peak periods of winter. Off-peak and standard periods are categorized together in this work as non-peak periods.

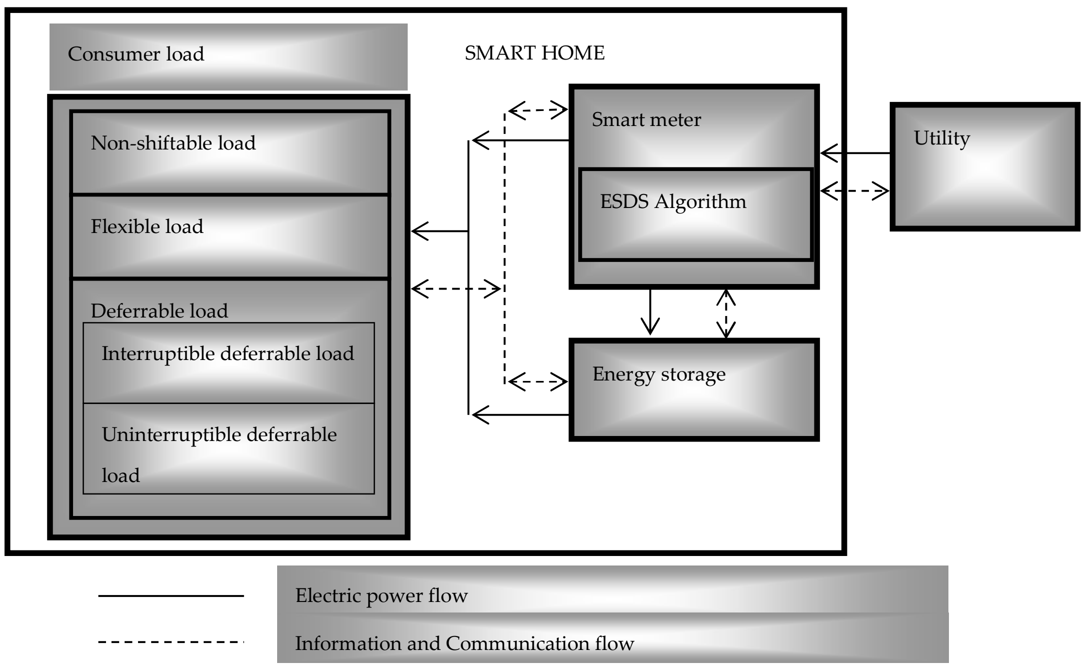

Figure1. Proposed ESDS smart home model.

Table 1. TOU tariff for single phase domestic customers.

Period	Weekday Time (hrs)	Summer (c/kWh)	Winter (c/kWh)
Peak	07:00-10:00, 18:00-20:00	109.89	262.09
Standard	10:00-16:00, 20:00-22:00	86.93	104.65
Off-peak	23:00-05:00	68.39	73.38

4. ESDS Problem Formulation

The ESDS problem formulation is detailed in this section.

4.1. Household Appliance Consumption Model

Let every smart home $a \in \mathbb{A}$, where $\mathbb{A} = [1,2,\ldots,A]$ in the smart grid with in-home storage facilities possess non-shiftable and shiftable smart appliances. A non-shiftable appliance $i \in \mathbb{I}$ is assumed to be a non-schedulable appliance (e.g. lighting, cooking, television etc.). The shiftable appliances are further classified as flexible (power-shiftable) and deferrable (time-shiftable) appliances. A flexible appliance $j \in \mathbb{J}$ is a smart appliance whose power consumption levels can be shifted (e.g. air-conditioner, space heater etc.) in response to tariff and consumer demand satisfaction, while a deferrable appliance is a smart appliance whose energy consumption can be shifted in time in response to tariff and consumer demand satisfaction. A deferrable load can either be uninterruptible or interruptible deferrable load. The uninterruptible deferrable load (e.g. dish washer, washing machine etc.), $f \in \mathbb{F}$ is the type of load whose operation start times can be shifted in time, but same duration of operation is still experienced by the appliance. While the interruptible deferrable appliance (e.g. pool pump, clothes dryer etc.), $l \in \mathbb{L}$ can have certain task interrupted during operation and scheduled to continue later. Therefore, let all the household smart appliances belong to $\mathbb{G} = \mathbb{I} \cup \mathbb{J} \cup \mathbb{F} \cup \mathbb{L} = \mathbb{I} \cup \mathbb{H}$, where $\mathbb{H} = \mathbb{J} \cup \mathbb{F} \cup \mathbb{L}$. The total load $x_{a,t}$ of consumer a at any time, $t \in \mathbb{T}$, where $\mathbb{T} = [1, 2, \ldots, \mathfrak{t}]$ is given by:

$$x_{a,t} = \sum_{i \in \mathbb{I}} x_{a,i,t} + \sum_{h \in \mathbb{H}} x_{a,h,t}\,, h = \{j, f, l\}, \forall t \in \mathbb{T}. \tag{1}$$

Also, the total schedulable load $x_{a,h,t}$ by all schedulable appliances $h \in \mathbb{H}$ at a given time t is expressed as:

$$x_{a,h,t} = \sum_{j \in \mathbb{F}} x_{a,j,t} + \sum_{f \in \mathbb{F}} x_{a,f,t} + \sum_{l \in \mathbb{E}} x_{a,l,t}\,, \forall t \in \mathbb{T}. \tag{2}$$

The load vector for all households in the smart grid $\mathbf{x} = [\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_a, \ldots, \mathbf{x}_A]$ and the daily load vector for each consumer $\mathbf{x}_a = [x_{a,1}, x_{a,2}, \ldots, x_{a,\mathfrak{t}}]'$, while its total daily load is expressed as:

$$x_a = \sum_{t \in \mathbb{T}} x_{a,t}\,, \forall a \in \mathbb{A}. \tag{3}$$

Assume the feasible period of operation $\mathcal{T}_{a,g}$ of any appliance g in the household has a start time $t_{a,g}^s$ and end time $t_{a,g}^e$, where $\mathcal{T}_{a,g} = \{t | t_{a,g}^s \le t \le t_{a,g}^e\}$, $g = \{i, j, f, l\}$, $\forall g \in \mathbb{G}$. Then, total energy $e_{a,g}$ consumed by any appliance $g \in \mathbb{G}$ during its feasible period of operation is given by:

$$e_{a,g} = \begin{cases} \sum_{t_{a,g}^s}^{t_{a,g}^e} x_{a,g,t}\,, & \forall t \in \mathbb{T}, g = \{i, j, f, l\}, \forall g \in \mathbb{G} \\ 0, & \forall t \in \mathbb{T} \backslash \mathcal{T}_{a,g},\ g = \{i, j, f, l\}, \forall g \in \mathbb{G} \end{cases}. \tag{4}$$

Therefore, the energy balance in the smart grid is given by:

$$\sum_{t \in \mathbb{T}} x_t = \sum_{a \in \mathbb{A}} \sum_{g \in \mathbb{G}} e_{a,g}\,, g = \{i, j, k, l\}. \tag{5}$$

Power level constraint for each smart appliance $g \in \mathbb{G}$ is in a smart home is given as:

$$x_{a,g}^{min} \le x_{a,g,t} \le x_{a,g}^{max}, g = \{i, j, f, l\}, \forall t \in \mathcal{T}_{a,g}, \tag{6}$$

where $x_{a,g}^{min}$ and $x_{a,g}^{max}$ define the minimum power level (OFF or standby mode) and maximum power level of each smart appliance respectively. Also, $x_{a,g}^{min} \ge 0$ and $x_{a,g}^{max} > 0$.

4.2. Consumer Dissatisfaction Cost Model

4.2.1. Power Shiftable Loads

The consumer will incur some dissatisfaction cost each time it attempts to shift the power level of its flexible loads from its nominal load $u_{a,j,t}$ to an actual load $x_{a,j,t}$. If the degree of dissatisfaction of a flexible load that is tolerable to the consumer is $\alpha_{a,j}$, then dissatisfaction cost $\bar{d}_{a,j}^t$ is expressed in (7) by modifying satisfaction cost in [2]:

$$\bar{d}_{a,j}^t = \alpha_{a,j} \left(u_{a,j,t} \theta_t \left[1 - \left(\frac{x_{a,j,t}}{u_{a,j,t}} \right)^{\gamma_t} \right] \right), \ \forall j \in \mathbb{J}, \tag{7}$$

where $0 \le \alpha_{a,j} \le 1$, $\gamma_t, \theta_t \in \mathbb{R}, \gamma_t < 1$, $\gamma_t \theta_t < 0$. The values of $\alpha_{a,j}, \gamma_t$ and θ_t are varied to model different levels of consumer dissatisfaction.

4.2.2. Time Shiftable Loads

This shall be considered for both uninterruptible and interruptible loads. The dissatisfaction cost of uninterruptible deferrable loads $\bar{d}_{a,f}^t$ in this model is expressed as a function of the delay/haste dissatisfaction in starting the task and the measure of tolerance $\alpha_{a,f}$ of such delay/haste to the consumer is given as:

$$\bar{d}_{a,f}^{t} = \alpha_{a,f}\left|t_{a,f}^{s,s} - t_{a,f}^{s}\right|,\ 0 \le \alpha_{a,f} \le 1, \forall f \in \mathbb{F}, \quad (8)$$

where $t_{a,f}^{s,s}$ and $t_{a,f}^{s}$ are the actual start time and nominal start time of the uninterruptible deferrable load respectively. A high delay/haste tolerance factor, $\alpha_{a,f}$ indicates the consumer is able to tolerate high dissatisfaction due to the delay/haste task execution and vice versa. Hence, $\alpha_{a,f}$ can be used to model different levels of consumer's dissatisfaction of uninterruptible deferrable loads. If the operation was scheduled by the ESDS to start before the nominal task start time, it is considered a haste task, while if it occurs after, it is regarded as a delay task. For uninterruptible deferrable loads, the actual feasible operation period $\mathcal{T}_{a,f}^{s} = \{t | t_{a,f}^{s,s} \le t \le t_{a,f}^{e,s}\}$. To ensure that the operation of an uninterruptible smart appliance continues once it starts without being interrupted, then the actual end time $t_{a,f}^{e,s}$ for the scheduled task is constrained by:

$$t_{a,f}^{e,s} \ge t_{a,f}^{s,s} + \eta_{a,f},\ \forall f \in \mathbb{F}, \forall t \in \mathbb{T}, \forall a \in \mathbb{A}. \quad (9)$$

where nominal task duration $\eta_{a,f} = |t_{a,f}^{e} - t_{a,f}^{s}|$.

For interruptible deferrable loads, the actual feasible period $\mathcal{T}_{a,l}^{s} = \{t | t_{a,l}^{s,s} \le t \le t_{a,l}^{e,s}\} = \mathcal{T}_{a,l}^{s_1} + \mathcal{T}_{a,l}^{s_2} + \ldots + \mathcal{T}_{a,l}^{s_q}$, where $\mathcal{T}_{a,l}^{s_1}, \mathcal{T}_{a,l}^{s_2}, \ldots, \mathcal{T}_{a,l}^{s_q}$ are possible durations of q number of scheduled sub-tasks within the entire task duration. If the actual entire task duration $\eta_{a,l}^{s} = |t_{a,l}^{e,s} - t_{a,l}^{s,s}|$ and the nominal task duration $\eta_{a,l} = |t_{a,l}^{e} - t_{a,l}^{s}|$, then the dissatisfaction cost $\bar{d}_{a,l}^{t}$ on interruptible deferrable load is also related with its tolerance factor $\alpha_{a,l}$ by:

$$\bar{d}_{a,l}^{t} = \alpha_{a,l}\,|\eta_{a,l} - \eta_{a,l}^{s}|,\ \ 0 \le \alpha_{a,l} \le 1, \forall l \in \mathbb{L}. \quad (10)$$

The values of $\alpha_{a,j}$, $\alpha_{a,f}$ and $\alpha_{a,l}$ are adjustable and can vary from one appliance to another and also from one consumer to another. The total hourly dissatisfaction cost $\bar{d}_{a}^{t}$ in a consumer premise following from (7), (8) and (10) is given as:

$$\bar{d}_{a}^{t} = \bar{d}_{a,j}^{t} + \bar{d}_{a,f}^{t} + \bar{d}_{a,l}^{t}, \forall a \in \mathbb{A}. \quad (11)$$

The total daily dissatisfaction cost $\overline{d_a} = \sum_{t \in \mathbb{T}} \bar{d}_{a}^{t}$.

4.3. Battery Storage Model

Let $b_{a,t}$ be the energy stored in the battery at any time $t \in \mathbb{T}$ in consumer $a \in \mathbb{A}$ premise. The daily energy storage scheduling vector $\mathbf{b}_a = [b_{a,1}, b_{a,2}, \ldots, b_{a,\mathrm{t}}]'$. Also, $b_{a,t} = b_{a,t}^{+} - b_{a,t}^{-}$, where $b_{a,t}^{+}$ is the energy charging profile and $b_{a,t}^{-}$ is energy discharging profile, and $b_{a,t}^{+}, b_{a,t}^{-} \ge 0$. Example of specifications for in-home battery can be found in [13].

Due to the conversion losses of the storage device, the charging efficiency β_a^{+} and discharging efficiency β_a^{-} fulfil conditions $0 < \beta_a^{+} \le 1$ and $\beta_a^{-} \ge 1$ respectively [8]. Therefore, if $b_{a,t}^{+}$ is the amount of energy consumed from the grid to charge the battery, it is only effectively charged with $\beta_a^{+} b_{a,t}^{+}$ amount of energy. Likewise if $b_{a,t}^{-}$ is required to be discharged from the battery to the smart appliances in the home then, only $\beta_a^{-} b_{a,t}^{-}$ is effectively discharged from the battery. The charging and discharging efficiency vector $\boldsymbol{\beta}_a = [\beta_a^{+}, -\beta_a^{-}]'$ and per-slot storage scheduling vector $\mathbf{b}_{a,t} = [b_{a,t}^{+}, b_{a,t}^{-}]'$. Then energy charged/discharged $\boldsymbol{\beta}_a' \mathbf{b}_{a,t}$ at time $t \in \mathbb{T}$ is related to the maximum charging rate b_a^{max} by:

$$\boldsymbol{\beta}_a' \mathbf{b}_{a,t} \le b_a^{max}. \quad (12)$$

The energy leakage rate λ_a of the battery is the rate of decrease in charge level on no-load and is bounded as $0 < \lambda_a \le 1$. Hence, the battery charge level $q_{a,t}$ reduces by $\lambda_a q_{a,t}$ at time $t+1$, but is related to the previous charge level $q_{a,t-1}$ at time $t-1$ by:

$$q_{a,t} = q_{a,t-1}(1 - \lambda_a) + \boldsymbol{\beta}_a' \mathbf{b}_{a,t}. \quad (13)$$

The charge level $q_{a,t}$ of the battery is bounded as:

$$0 \le q_{a,t} \le b_{cap}, \quad (14)$$

where b_{cap} is the battery capacity. Therefore, following from (13), (14), $\mathbf{b}_{a,t}$ can be constrained as:

$$-q_{a,t-1}(1-\lambda_a) \le \boldsymbol{\beta}_a^{\mathrm{T}} \mathbf{b}_{a,t} \le b_{cap} - q_{a,t-1}(1-\lambda_a). \quad (15)$$

Also, $q_{a,t}$ is related to the initial charge level q_{a,t_0} of the battery and its storage profilesby:

$$q_{a,t} = q_{a,t_0}(1-\lambda_{a,t}) + \sum_{t=t_0}^{t} \lambda_{a,t-t_0} \boldsymbol{\beta}_a^{\mathrm{T}} \mathbf{b}_{a,t}. \quad (16)$$

4.4. Grid Energy Consumption Model

The per-timeslot demand $Y_{a,r}^t$ and total daily demand $Y_{a,r}$ from the grid are given by (17) and (18):

$$Y_{a,r}^t = \begin{cases} x_{a,t} + b_{a,t}^+, & \forall t \in t_{np}, t_{np} \subset \mathbb{T} \\ (x_{a,t} - q_{a,t})^+, & \forall t \in t_p, t_p \subset \mathbb{T}' \end{cases} \quad (17)$$

$$Y_{a,r} = \sum_{t \in \mathbb{T}} Y_{a,r}^t, \forall t \in \mathbb{T}, \forall a \in \mathbb{A}, \quad (18)$$

respectively, where t_{np} and t_p are sets of non-peak and peak periods respectively. The ESDS algorithm uses energy price to determine the source of electricity to consumer appliances at every time $t \in \mathbb{T}$. It reads the energy stored in the battery at the price that the energy was brought from the grid and compares it with the utility block TOU price and chooses the lower price in order to minimize consumer's energy expenditure. Hence, more consumer load is permitted to be scheduled for the peak period within the capacity of the energy stored in the battery. Therefore, the daily grid energy demand vector, $\mathbf{Y}_{a,r} = \left[Y_{a,r}^1, Y_{a,r}^2, \dots, Y_{a,r}^{\mathfrak{t}}\right]'$. The total demand from the grid by a household is bounded as:

$$0 \le Y_{a,r}^t \le Y_{a,r}^{t,max}, \ \forall t \in \mathbb{T}, \forall a \in \mathbb{A}. \quad (19)$$

The maximum load $Y_{a,r}^{t,max}$ is dependent upon the fuse/line capacity or as determined by the utility for each household. Also, since the batteries are not feeding the grid then:

$$x_{a,t} + b_{a,t} \ge 0, \forall t \in \mathbb{T}, \forall a \in. \quad (20)$$

4.5. Energy Expenditure Model

Energy expenditure to the consumers C_a^t is a function of the total energy consumed from the grid$Y_{a,r}^t$ and the TOU price P_t, where $\mathbf{P} = [P_1, P_2, \dots, P_{\mathfrak{t}}]'$atevery time t. Therefore, the hourly and daily energy expenditure, C_a^t and C_a,are respectively given as follows:

$$C_a^t = P_t Y_{a,r}^t, \quad (21)$$

$$C_a = \sum_{\forall t \in \mathbb{T}} C_a^t. \quad (22)$$

4.6. The ESDS Optimization Problem

The objective function in the ESDS algorithm is to minimize total demand from grid, energy expenditure and dissatisfaction cost for each consumer. A convex programming problem was formulated as shown in (23), which can be solved using the interior point method [14]:

$$\min_{C_a^t, \bar{d}_a^t \in \mathbb{R}} C_a^t + \bar{d}_a^t$$

$$\text{s.t.} (1), (4)-(6), (9), (12), (14)\text{–}(17), (19), (20). \quad (23)$$

4.7. PAR Demand Model

The effect of the ESDS algorithm was also investigated on PAR demand since it has potentials to reduce peak period demand from the grid. The PAR demand is given by:

$$PAR = \frac{Peakdemandfromgrid}{Averagedemandfromgrid} = \frac{\max_{t \in \mathbb{T}} \sum_{a \in \mathbb{A}} Y_{a,r}^t}{\frac{1}{\mathfrak{t}} \sum_{a \in \mathbb{A}, t \in \mathbb{T}} Y_{a,r}^t}. \quad (24)$$

Since the denominator of (24) is approximately constant then (24) can be simplified and solved as a linear program using the simplex method [15].

5. Simulation Results and Discussions

Household energy consumption data for 100 flats were obtained from [16] and fed into the ESDS algorithm for three scenarios namely: No DSM – Scenario 1, DSM without ESDS – Scenario 2 and DSM with ESDS – Scenario 3. Scenario 1 does not involve any optimization at all, as it is the obtained nominal consumption of the consumers. Scenario 2 solves (22) excluding all battery-related constraints, while Scenario 3 carries out the complete optimization problem as shown in (22).

The results of average hourly energy consumption and expenditure from the grid for flats5 and 12 chosen at random during summer are presented in Figure2. It can be seen from Figure2 that Scenarios 2 and 3 outperformed Scenario 1 for both flats because of the optimization scheduling involved in their algorithms. However, Scenario 3 outperformed Scenario 2 for both flats. The household consumed least energy from the utility grid during morning and evening peak periods under Scenario 3 since the battery was the primary source of energy at peak periods. This therefore, led to reduced energy consumption from the grid during peak periods and consequently, reduced energy expenditure and increased financial savings for the consumers. The energy consumed from the battery at peak time by the scheduled appliances is the energy bought from the grid at a non-peak (off-peak and standard periods) TOU (low) prices. Also, the aggregate energy consumption profile for the one hundred households is presented in Figure 3.

Hence, Scenario 3(ESDS) algorithm would offer the consumers more financial savings than the Scenario 2algorithm.Average monthly energy expenditure in South African rands (R) for seven out of the twenty consumers chosen at random is presented in Figure4. Therefore, the consumers under Scenarios 2 and 3 algorithms were able to reduce their average energy expenditure, compared to Scenario 1. However, the financial savings on energy expenditure was higher for the consumers in Scenario 3 than Scenario 2 due to the possession of DES in consumers' premises. The average monthly financial savings for all the households in Scenarios 2 and 3 are 27% and 53% respectively.

Energy consumption scheduling in consumers premise has known advantages, but not without the disadvantage of demand dissatisfaction. However, the implementation of DES in ESDS algorithm proposes reduced or negligible demand dissatisfaction cost. In terms of the dissatisfaction cost, it was observed that Scenario 3 offered lesser dissatisfaction to consumers than Scenario 2 especially at peak periods. This is because the consumers under Scenario 3 had purchased energy from the grid at non-peak times (low energy price periods) and stored it in their batteries. This stored energy is discharged locally to household appliances during morning and evening peak periods primarily, and thereby mitigate peak period demand dissatisfaction that characterizes the Scenario 2 scheduling algorithm like other DSM energy scheduling algorithms in literature [4], [5], [7].The effect of DSM scheduling in Scenarios 2 and 3 on dissatisfaction cost is shown in Figure5.Dissatisfaction cost was not considered for Scenario 1 because it was the consumer's traditional nominal consumption without energy scheduling and hence, has no demand dissatisfaction cost.

The flexible appliances generates positive, negative and zero demand dissatisfaction, while the deferrable appliances generate either positive or zero dissatisfaction depending on the load scheduling. Positive total daily dissatisfaction is not desirable for maximized consumer's welfare. The desirable total daily dissatisfaction $\bar{d}_a$ for a consumer should be $\bar{d}_a \leq 0$ for consumer's maximum social welfare and minimized energy expenditure. The simulation results showed that the average daily dissatisfaction for Scenarios 2 and 3 are1.386 kWh and -1.065 kWh respectively. This implies that the integration of the battery into the consumer's premise offered reduced or negligible dissatisfaction to the consumers.

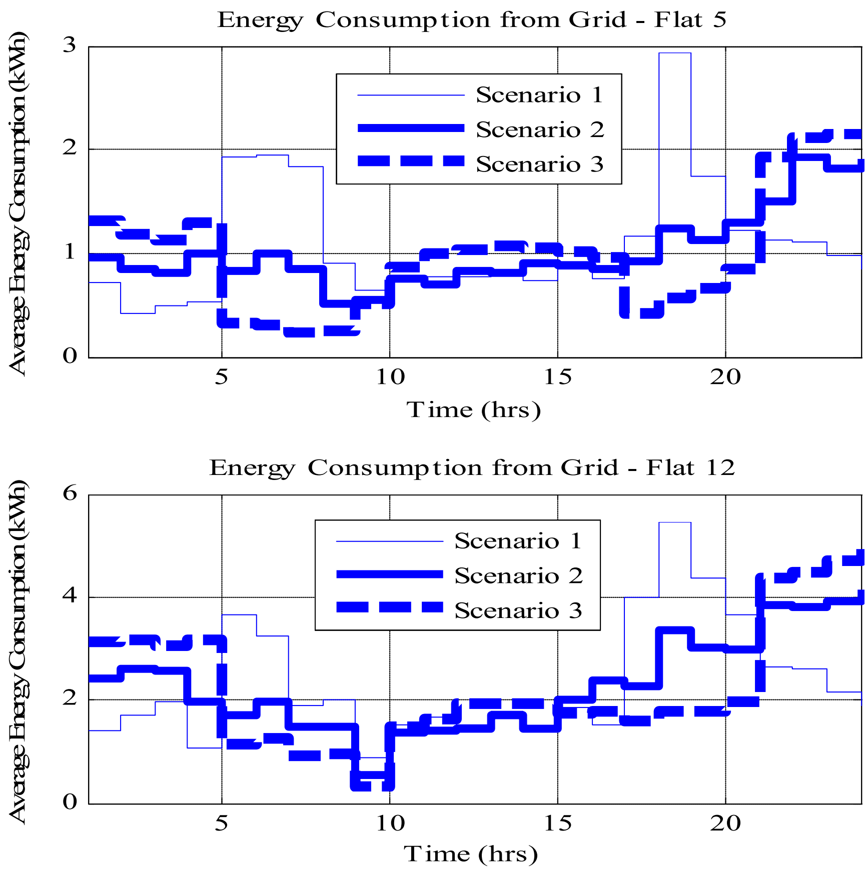

Figure 2. Average hourly energy consumption from grid by selected flats

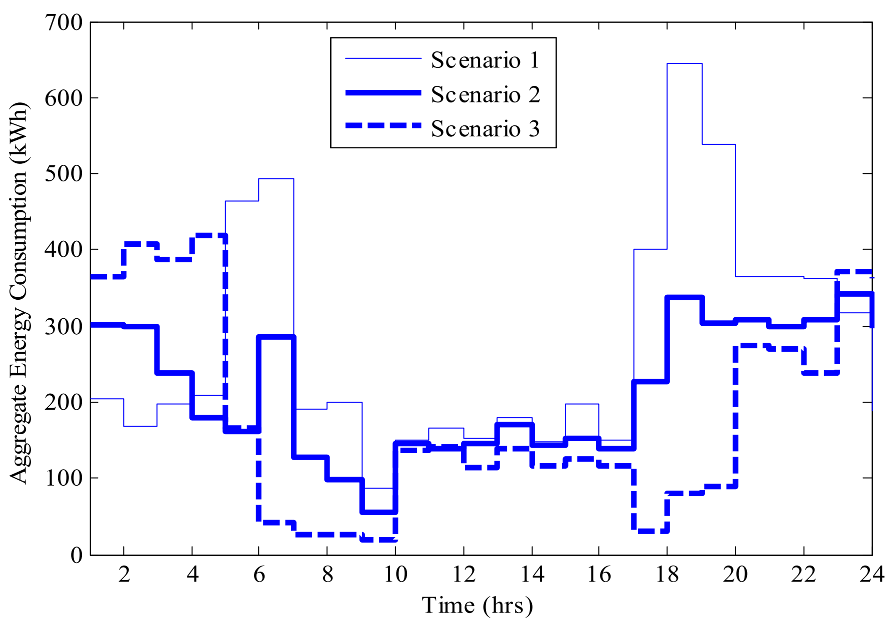

Figure 3. Aggregate hourly energy consumption

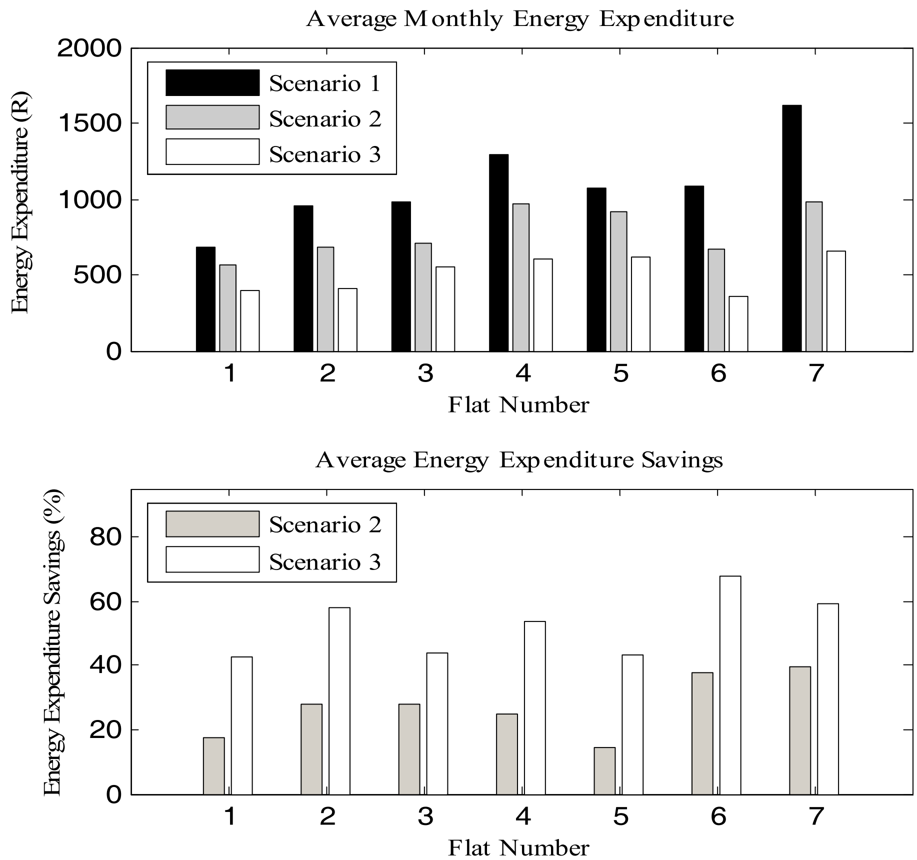

Figure 4. Average energy expenditure and financial savings for selected household

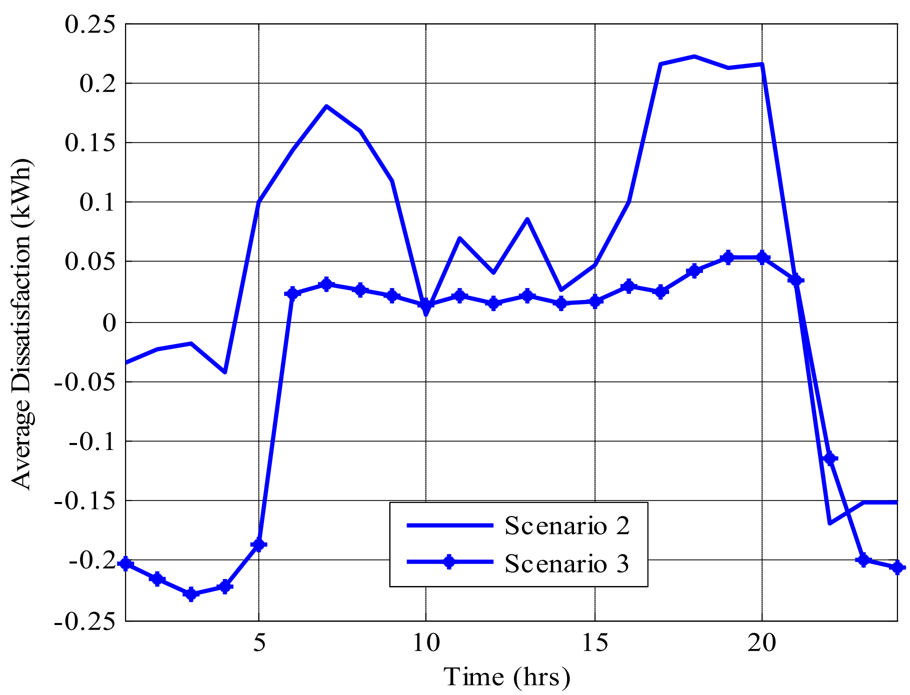

Figure 5. Comparison of energy dissatisfaction between Scenarios 2 and 3

Also, further sensitivity analysis was carried out to investigate the effect of battery capacity on consumer's dissatisfaction. It was discovered that the higher the battery capacity acquired by a consumer, the lesser it will be dissatisfied by appliance scheduling with respect to its average peak period demand. However, battery capacity cannot indefinitely increase; otherwise, the law of diminishing returns would set on financial savings and battery pay-back period. The battery capacity assumed initially in the simulation was 7 kWh. Therefore, the effects of 4 kWh and 10 kWh battery capacities on demand dissatisfaction were studied and the results found are presented in Figure6. The average daily demand dissatisfaction obtained were 0.063 kWh, -1.265 kWh and -4.217 kWh for the 4 kWh, 7 kWh and 10 kWh batteries, respectively. This implies that the 10 kWh battery capacities would not be economical for the consumers whose consumption data was simulated in this work due to very high satisfaction. However, the consumer can choose between the 4 kWh and 7 kWh batteries depending on its tolerance to dissatisfaction. From interpolation, it was observed that zero dissatisfaction can be achieved with approximately 5 kWh battery capacity.

Hence, there is a need for consumers to seek technical advice before purchasing an in-home energy storage device for optimized satisfaction and energy expenditure. Also, the total daily morning or evening peak period demand can be used to determine the size of battery capacity.

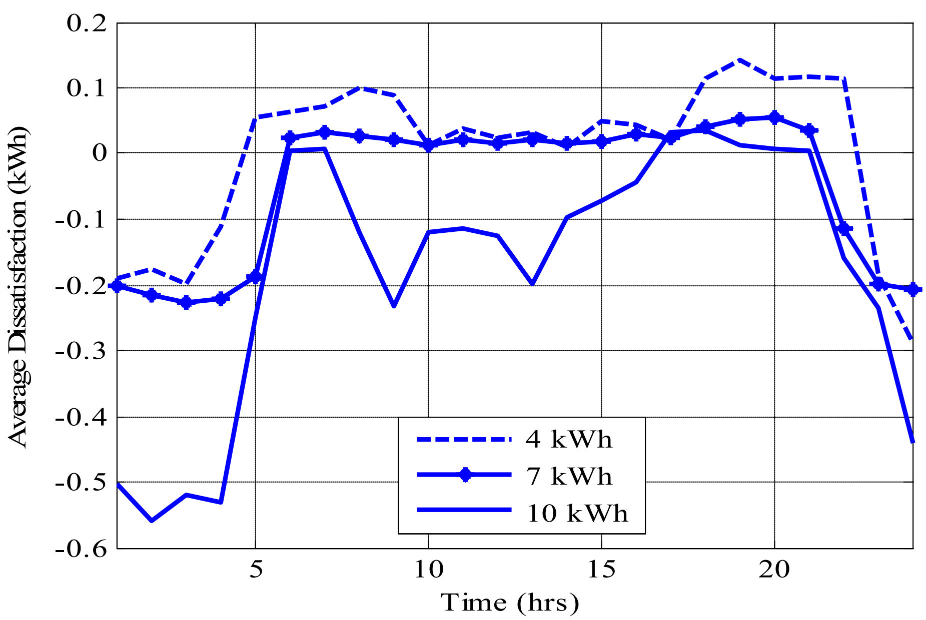

Figure6. Relationship between battery capacity and dissatisfaction cost

The average PAR demand for Scenarios 1, 2 and 3 was found to be 1.961, 1.675 and 1.154, respectively, which are less than the results obtained in [6]. Therefore, Scenario 3 would offer the utility grid better stability and reliability than others due to its lowest grid peak demand and PAR demand.

The relationship between number of ESDS smart homes in the smart grid and PAR demand was also investigated and the result is presented in Figure7. This sensitivity analysis was carried out on PAR demand because it may not be a realistic assumption that all the smart homes in a smart microgrid or smart grid at large would have battery storage facilities installed in their premises for DSM purposes. And as can be seen from Figure7, the higher the number of ESDS smart homes in a smart grid, the lower the PAR demand of the smart grid.

The relationship between battery capacity and aggregate PAR demand is presented in Figure8 and it shows that the higher the battery capacity of the iHES device, the lower the aggregate PAR demand from the grid. This was simulated for no battery (i.e. 0 kWh), 4 kWh, 7 kWh and 10 kWh battery capacities.

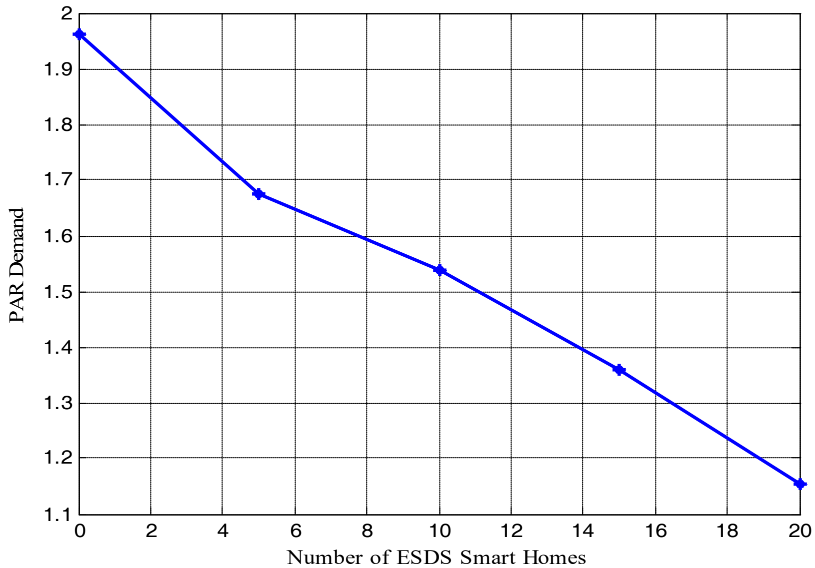

Figure7. Relationship between number of ESDS smart homes and aggregate PAR demand

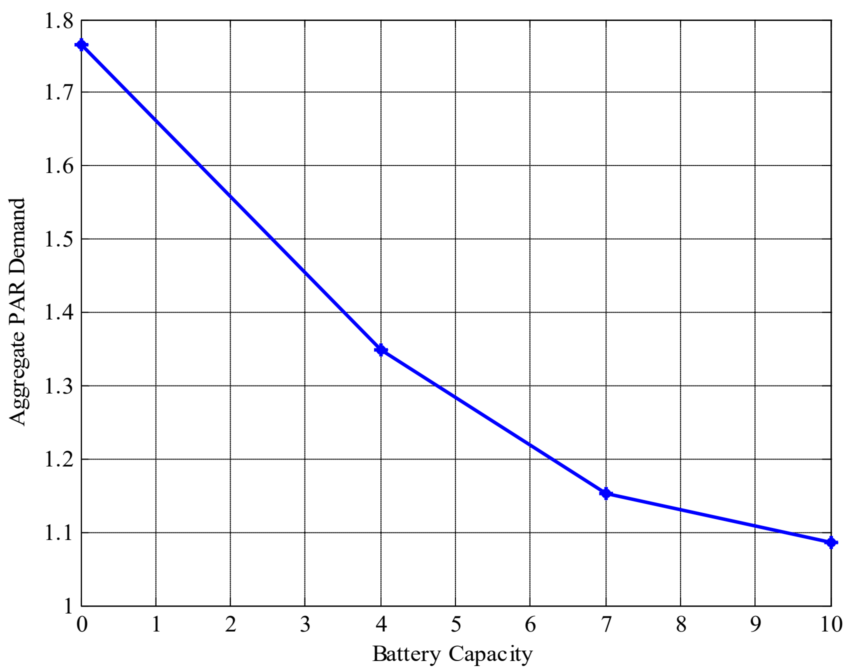

Figure8. Relationship between battery capacity and aggregate PAR demand

The computational complexity involved in the ESDS algorithm is not beyond what can be solved in polynomial real time with an average computational time of 1.15s depending on computer configuration. It can also be implemented into an embedded energy controller chip. Work is on-going on that in our laboratory. Practical implementation of the algorithm will be presented in future work. Limited security risk may however arise from the utility during communication.

Although the ESDS algorithm was tested for a TOU pricing scenario, it can also find application in a Real Time Pricing (RTP) environment by upgrading its pricing and demand response intelligence. Fundamentally, utilities set real time energy price based on the aggregate demand obtained from load schedule or forecasting. Therefore, energy prices are high at high demand periods and low at low demand periods. Hence, since the ESDS algorithm could minimize $Y_{a,r}^{t}$, then it can also be used to obtain reduced grid energy consumption, energy price and expenditure for RTP consumers also. Such a work as the ESDS offers contribution towards the sustainability of the grid and environment by reducing peak energy demand from the grid [17] and offering low carbon footprint [18].

6. Conclusion

This work has studied the effect of DES in a smart grid for reduction in consumer peak period demand dissatisfaction and energy expenditure by solving a convex optimization problem called ESDS algorithm. Three scenarios were considered for analyses – No DSM (Scenario 1), DSM without ESDS (Scenario 2) and DSM with ESDS (Scenario 3). Scenario 3 enabled the consumers to consumed energy during peak period at the lower price (off-peak or standard period prices) that the energy was initially bought from the grid and stored in the battery. Hence, little or no consumer demands to be scheduled for consumption from the grid at peak periods thereby enhancing consumers' satisfaction. The numerical results showed that the Scenario 3 outperformed other scenarios in energy savings, financial savings, reduced and negligible peak period demand dissatisfaction and PAR demand reduction. The proposed ESDS algorithm can offer consumer privacy and reduced security risk because each smart meter communicates directly to the utility, but not to other participating consumers in the network. The ESDS algorithm is shown to be a consumer-friendly, grid-friendly, financial-friendly, societal-friendly and environmental-friendly DSM solution for the smart grid. Although the ESDS model has been shown for residential consumers in this work, it can also be modified and applied to commercial and industrial users.

Author Contributions: Omowunmi Longe, Khmaies Ouahada and Ashot N. Harutyunyan conceived and designed the problem formulation; Omowunmi Longe designed the simulation software and wrote the paper; while all the authors were involved in data analysis, result validation and editing of the paper.

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