ENERGY OPTIMIZATION FOR A SMART PROSUMER

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Abstract
This paper outlines the optimization of cost of electrical energy consumption for a small microgrid typical of a residential area where each household has renewable generation capability and the daily load is portioned into essential none-interruptible and schedulable or interruptible loads. Dual tariffs exist, for buying and the other for in-feed into the utility grid. The optimization makes appliances scheduling decisions to suit prevailing power availability as well amount of power to sell or procure from the utility depending on availability and prevailing real time pricing. We assume availability of time-variant energy parameters, then formulate a global optimization problem whose solutions leads to quantification of the optimal amount of energy purchased and sold for each of the individual households. When the unrealistic assumption of availability of information is removed from the implementation of the global optimization, an online algorithm that only requires the current values of the time varying supply and demand processes shows by simulation that the distributed algorithm can realise credible scheduling of prosumer household electricity usage. This is imperative as the very requirement of involving the consumer for appliances scheduling defeats the optimization cause as humans are not suitable for such repetitive and mundane tasks.

Keywords: electric energy cost, optimization, renewable generation and smart grid.

Introduction

\The per capita global electrical energy consumption has continuously risen since the 1960s in all economic sectors, commercial, residential sector [1], Figure 1. The residential sector amounted to an average of 30% of the overall electric energy consumption, while the consumption in all buildings represented about 40% [2][3] . The residential electrical loading is key in the context of the emerging Smart Grid (SG) paradigm consumption value chain and energy management methodologies riding on emergent technologies and innovation [4][5]. The focus of the SG control approaches is on technical, economical and identifying the possibilities of incentivizing the Consumer. In most countries growing electricity demand is now limited by generation infrastructure due to aging, capacity and pollution inhibiting factors. The concept of smart grid inclusive of clean Renewable Energy Sources (RES) has emerged [6].

Full potential of the SG is enabled by ICT communication which enables Demand Side Management (DSM) to be implemented combined with Home Energy Management Systems (HEMS), [7][8]. Residential energy management aims to decrease the electricity costs and also reduce the Peak-to-Average Ratio (PAR). In using tariffs DSM encourages prosumers to reduce or shift consumption to off-peak hours. This is achieved by scheduling the energy obtained from the grid and internal RES elements according to some optimization criterion such that essential or none-interruptible (NI) loads are met instantly and run to the full operational cycle without interruption. NI loads cannot be easily rescheduled to operate at other time slots. However, they can be feed from RES for which peak hourly consumption or power is optimized. Schedulable loads or interruptible can be moved to times of low energy demand hence attractive tariffs. The advantages of the SG are increased footprint of RES such as wind, solar and flexibility enabled by DSM. Electricity generated by prosumers from RES helps the prosumer to save on electricity costs and in systems where grid in-feed is possible through net metering, a 'profit' or credit can be made by feeding the excess renewable energy back into the grid [9].

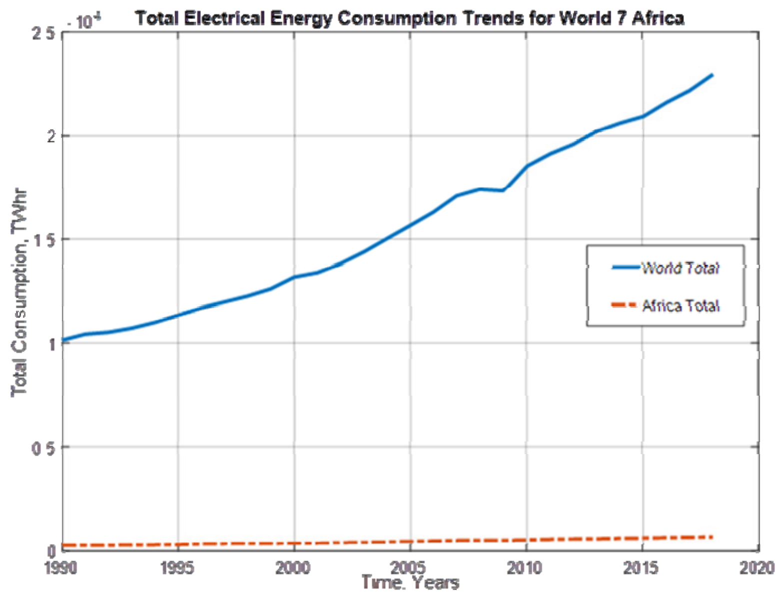

Figure 1: World/Africa TWhr Consumption Trend

The great shortcoming of renewable energy sources is supply uncertainty due to the random natural weather elements [10] as they impact generation. It is therefore imperative to adopt hybrid systems [11], or provide a mixture of traditional sources of power and storage to mitigate renewables climate induced random phenomenon [12][8].

Another strategy for mitigating volatility of the renewables is Demand Response (DR) which works through flexible [9] [10] consumer's incentives to curtail load or shift consumption to off-peak periods. The renewable power supplies are deployed to deliver the energy when it is available, [10] within specific time windows. Energy management strategies aim to maximize usage of energy drawn from the renewable sources and minimize energy drawn from the utility grid. When excess renewable energy is available consumers can feed into the grid at an in feed rate as determined by the appropriate utilities.

A number of DSM tariff regimes exist based on time of day and seasonal variations. Some tariffs define energy cost every hour or every 24 hours in advance. The 24 hour billing period is segmented into time intervals such as peak time. This is when consumption is very high. Off-peak time is when consumption is low and mid-peak corresponds to mid-intervals between the two extremes. Should contingency events occur, consumers are billed at maximum rates than any other times as the stability of an entire system can be compromised. The preva-

lent tariffs are Time of Use (TOU) Pricing, Real Time Pricing (RTP), Critical Peak Pricing (CPP) and Flat Rate Pricing (FRP).
Time of Use (TOU) Pricing: In this pricing tariff the day is split into low, high or mid tariff time periods and prices are predetermined depending on the season or month whereby the on-peak time periods have the highest electricity rates [2][3]. Other countries have multi-segments of these time slots. Real Time Pricing (RTP): RTP signal is also similar to TOU when prices change hourly. At times when energy demand is high, price will be correspondingly high and the converse applies. Critical Peak Pricing (CPP): CPP significantly increases the price when system is constrained and lowers the prices on non-constrained or normal days of the year [4]. Flat Rate Pricing (FRP): Utility charges a fixed rate for energy instead of charging by the hour.
This paper looks at minimizing electrical energy cost for a prosumer on real time pricing tariff and on-board or local renewable generation. Each consumer in its load mix has essential appliances (NIA) i.e. the non-shiftable and shiftable ones (IA) [13]. Thus essential or must run and shiftable loads are the two predominant load types. Cost reduction consists of scheduling suitable loads to run during times of favourable tariffs as determined form the RTP signals from the utility, minimizing purchases from the utility or conversely maximizing utilization of local RES and finally maximizing the amount of energy transacted to the grid on favourable tariffs. In this pursuit we formulate the optimization problem from which we deduce the optimal electricity consumed, sold and purchased for each prosumer whiles assuming the knowledge of current and future modelling parameters. Cognisant of the limitations of the assumption on availability of model parameters a distributed online algorithm based only on current values of the time-varying supply and demand processes is formulated. The simulation results show that the proposed strategy can be effective for optimizing energy consumption.
The outline of the paper is as follows. In Section II, models for RES are summarised. The formulation for the optimization problem with known parameters is outlined in Section III. The Lyapunov optimization based online algorithm is presented in Section IV. Section V deals with a short case study simulation results of the optimization method outlined and the paper is concluded in Section VI.

PV and Wind Turbine Modeling

For a realistic PV model, various OEP data is required. Weather parameters within a given locality are freely available from various national online weather data for download [12]. The same applies to the wind parameters. First we present the models for the distributed energy sources i.e. PV and Wind Turbine (WT) generators. Definitions;

A: PV and Wind Turbine Models

PV Generator Model: The PV generations depends on several factors for instance weather conditions as daily irradiance, seasonality, number of PV module cells, temperature etc. Since irradiance is stochastic, the generation of the PV can be described by a stochastic pdf model. The Beta bimodal distribution function (1) is used [14];

$$f_{pv}(s) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\cdot\Gamma(\beta)} \cdot s^{\alpha-1} \cdot (1-s)^{\beta-1}, 0 \le s \le 1; \beta \ge 0 \\ 0 \end{cases} \tag{1}$$

where , $\alpha = \frac{\mu\beta}{1-\mu}$ and $\beta = (1-\mu)\left(\frac{\mu(\mu+1)}{\sigma^2} - 1\right)$

The parameters α and β, determine the shape of the Beta distribution function $f(s)$. Solar irradiance is represented by s in kW/m^2. μ nd σ^2 denote the mean and variance of the solar irradiance. Output power of the PV module is dependent on the solar irradiance and site ambient temperature as well as the characteristics of the PV module.

Table 1. Model Parameters

Parameters	**PV & WT Source Parameters**
	Description
N , F_{ff}	*Number of PV cells and fill factor*
V_{mpp}	*Cell output voltage at maximum power point.*
I_{mpp}	*Module current at maximum power point.*
V_{OC} , I_{sc}	*PV open circuit voltage and PV short circuit current*
k_v, k_i	*Voltage and current coefficients*
T_{cell}	*Cell temperature.*
T_a , T_N	*Ambient temperature & Nominal operating temperature on degrees Celsius.*
P_r	*WT rated power output*
v_{in} , v_{out}	*WT cut-in speed and WT rated speed, m/s.*

For a given specific site the Beta pdf generates the solar irradiance at a specific time and the output power during the different states is estimated from (2):

$$P_{pv} = N \cdot F_{ff} \cdot V \cdot I \tag{2}$$

Whereby the parameter in (2) are defined by (3).

$$\begin{aligned} F_{ff} &= \frac{V_{mpp} \cdot I_{mpp}}{V_{OC} \cdot I_{sc}}, \quad V = V_{OC} - k_v \cdot T_{cell} \\ I &= s \cdot (I_{sc} + k_c(T_{cell} - 25)), \quad T_{cell} = T_a + s \cdot \frac{T_N - 20}{0.8} \end{aligned} \tag{3}$$

Wind Turbine Model: WT output depends on the wind speed profile. We use the Weibull pdf (4) to represent the wind speed profile [14].

$$f_w(w) = \begin{cases} \frac{v}{\lambda}\left(\frac{w}{\lambda}\right)^{v-1} \cdot Exp\left(-\frac{w}{\lambda}\right)^{v}, w \geq 0 \\ 0, otherwise \end{cases} \tag{4}$$

The Weibull distribution interpolates between the exponential and Rayleigh distributions and for certain values of v and λ, the Rayleigh distribution is closer to the wind distribution function. Based on estimated speeds the generated power from the wind can be estimated as follows;

$$P_w = \begin{cases} 0, v < v_{in}, v > v_{out} \\ P_r\left(\dfrac{v - v_{in}}{v_r - v_{in}}\right), v_{in} \le v \le v_r \\ P_r, otherwise \end{cases} \tag{5}$$

The WT power output dependents on the site wind speed as well as the manufacture power performance curve parameters. Once the Rayleigh pdf is generated for a specific time, the power output at the different states is calculated for that time interval as [5]. If solar irradiance belongs to the interval $s \in [s_1, s_2]$, the probability that irradiance s lies in this interval at a specific time interval is mathematically the cpf i.e., cumulative probability function which by integration is;

$$\Theta_{PV} = \int_{s_1}^{s_2} f_{pv}(s)ds \tag{6}$$

and similarly for the WT;

$$\Theta_{WT} = \int_{w_1}^{w_2} f_w(v)dv \tag{7}$$

Subject to $f_w(s) \ge 0$ and , $\int_0^{\infty} f_w(s)ds = 1$.

The pdf of each DG (6) and (7) can be divided into time periods in which solar irradiance and wind speed range within certain limits. For each such time period, there are a number of states for solar irradiance and wind speed. The joint probability of both irradiance and wind speed to be within the given intervals is given by the convolution assuming events are independent i.e,

$$\Theta = \Theta_{PV} * \Theta_{WT} \tag{8}$$

s_i and $v_i, i = 1,2$ are respective irradiance and wind speed limits in particular state. At any given time the total power P_{re} from both RES is governed by the probability (8) and subject to an upper limit, $P_{re,\max}$.

B: Smart Grid Model

The SG topology is depicted in Figure.2 and the basic ICT interfaces configuration. Essential appliances are none-interruptible and shiftable appliances' on-off times can be shifted to different time windows on the 24 hour optimization cycle. In the grid model, K i.e., $\mathrm{K} = \{1,2,...,k,k+1,...,N\}$ represents the set of consumers with cardinality N. The 24 hour day is divided into a uniform set of time slots H such that $\mathrm{H} = \{1,2,...,h,h+1,...,H\}$. To each prosumer is connected a Smart Meter (SM) incorporating an Energy Scheduling Controller (ESC). For the k^{th} household the set of appliances is A_k has cardinality N_k. Each appliance 'a' for k^{th} consumer, at the h^{th} hour time interval consumes $x_{k,a}^h$ energy. Over the 24-hours period the energy consumption vector $x_{k,a}$ for the k^{th} consumer's appliance 'a' is, $\left[x_{k,a}^1, x_{k,a}^2, ..., x_{k,a}^H\right]$.

From the utility side a centralized scheduler optimizes the entire system based on collective data it gathers from individual SM. The total energy consumption for k^{th} household at h^{th} time interval is,

$$l_k^h = \sum_{a \in A_k}^{N_k} x_{k,a}^h, \forall h \in \mathrm{H} \tag{9}$$

The total load for k^{th} consumer over the full time horizon is,

$$l_k = \sum_{h=1}^{\mathrm{H}} \sum_{a \in A_k}^{N_k} x_{k,a}^h, \forall h \in \mathrm{H} \tag{10}$$

Accordingly, the scheduled loading for k^{th} consumer is the set,

$$l_k = \left[l_k^1, l_k^2, \ldots, l_k^{H-1}, l_k^{\mathrm{H}} \right] \tag{11}$$

Taken over all the N consumers in the microgrids network, the utility sees an hourly load of;

$$U^h = \sum_{k \in K}^{N_k} l_k^h, \forall h \in \mathrm{H} \tag{12}$$

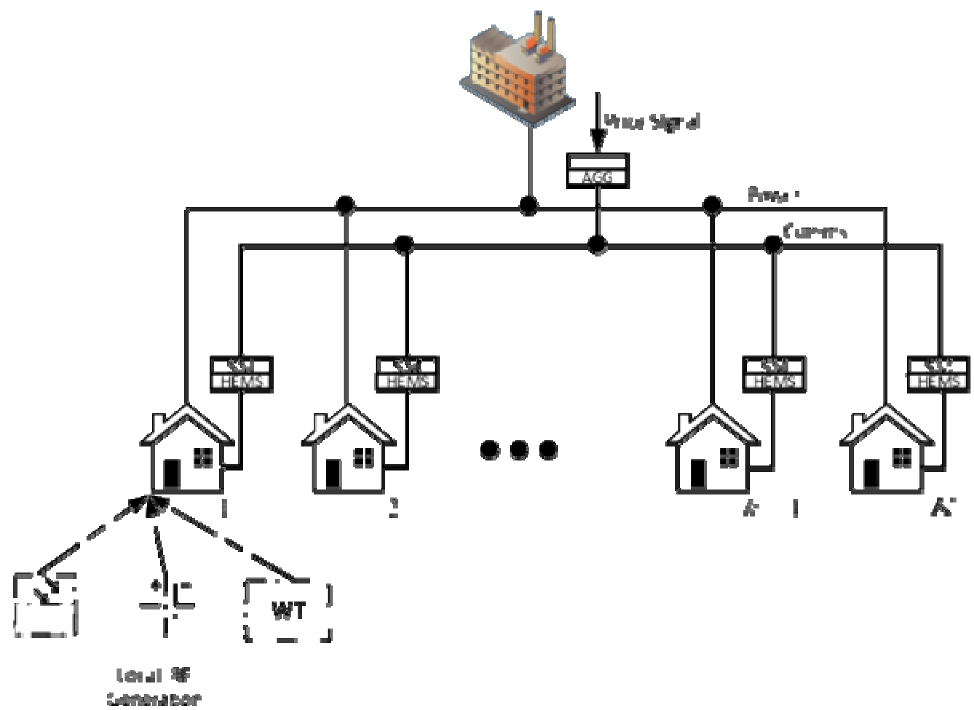

Figure 2. Smart Grid Model Outline

C: Model for Shiftable Load

An elastic appliance means it is flexible i.e. its power consumption pattern can be scheduled to different times. Elastic loads possess a flexible finishing time set by the user within certain consumption periods and specified power ratings. Refrigerator, HVAC, irons, washing machines, pool pumps, storage heating system etc., fall into this category. Let A_k^{sh} and N_{sh} represent the set and the cardinality of this set for k^{th} household. The start and stop time of shiftable appliance are confined to the time window, $H_{sh} = \lfloor \alpha_{k,a,start},....,\alpha_{k,a,end} \rfloor$ and the total power E_K^{sh} of all shiftable appliances for the k^{th} consumer is;

$$E_K^{sh} = \sum_{a \in A_{sh}}^{N_{sh}} \sum_{h=\alpha_{k,a,start}}^{\alpha_{k,a,end}} x_{k,a}^h \tag{13}$$

such that, $x_{k,a}^h \equiv 0, \forall h \notin H_{k,a}, a \in A_{sh}$.

For each appliances they is an upper and lower bound to the power consumption according to,

$$\gamma_{k,a}^{\min} \le x_{k,a}^h \le \gamma_{k,a}^{\max}, \forall h \notin H_{k,a}, a \in A_{sh} \tag{14}$$

D: Inellastic or None-Shiftable Load

Typical of none shiftable loads are luminaries, TVs and PCs. Energy consumption for these is fixed. Once they are required they must start and they is no elasticity in starting times. The set of inelastic loads is represented by A_k^{in} and N_{in} represents and the cardinality of this set for the k^{th} household. The start and stop time of none shiftable appliance is confined to the same time window $\mathrm{H} = \{1,2,...,h,h+1,...,H\}$. The total power of all none-shiftable appliances for the k^{th} consumer is;

$$E_k^e = \sum_{a \in A_{in}}^{N_{in}} \sum_{h=1}^{\mathrm{H}} \delta(h) \cdot x_{k,a}^h \tag{15}$$

Where $\delta(h)$ is 1 when the appliance is on otherwise it is zero if the appliance is off. The aggregate essential and shiftable load for all N users or households when time is t can be expressed as;

$$A_e(t) = \sum_{k=1}^{N} E_k^e(t), \quad A_s(t) = \sum_{k=1}^{N} E_k^{sh}(t) \tag{16}$$

E: Power Flow Modeling

In Figure.3, the LHS depicts two possible electrical power sources feeding a residential consumer. Energy is either sourced from the utility grid $P_g(t)$ or from the renewable generators $P_{re}(t)$. $P_p(t), P_e(t)$ and $P_s(t)$ are renewable power components sold to the grid, required to meet essential and a portion to feed the shiftable load. Similarly $P_{ge}(t)$ and $P_{gs}(t)$ are power components sourced from the utility grid to meet essential and shiftable load shortfalls respectively. The energy balance relationships for the renewable and utility generation can then be specified as in (17) and (18) respectively.

$$P_{re}(t) = P_p(t) + P_e(t) + P_s(t) \tag{17}$$

$$P_g(t) = P_{ge}(t) + P_{gs}(t), \quad 0 \le P_g(t) \le P_{\max} \tag{18}$$

Let $e_g(t)$ represent the tariff of the grid electricity at time t and define $e_p(t)$ as the feed-in tariff at time t as set by the utility. It follows that at any time t the cost of electricity to the prosumer is $P_g(t)\cdot e_g(t)$ less the benefit accrued from a portion of renewable energy feed into the grid (19).

$$C(t) = P_g(t)\cdot e_g(t) - P_p(t)\cdot e_p(t) \tag{19}$$

For each consumer as earlier stated they are essential and flexible or shiftable appliances or loads.

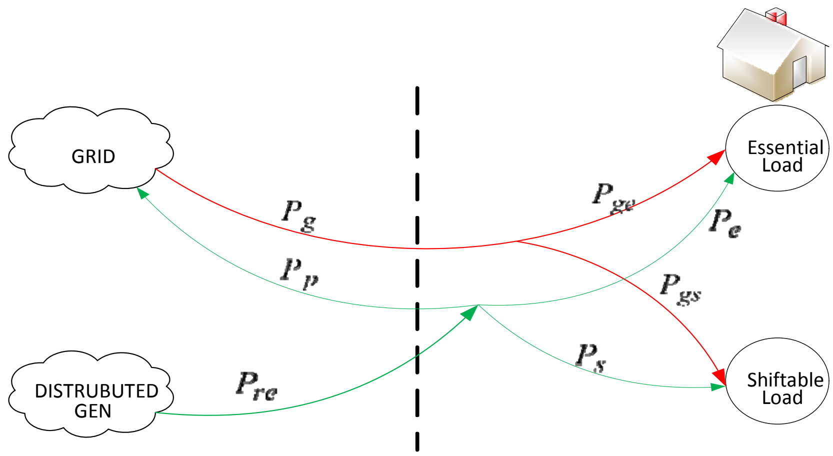

Figure 3. Microgrid Power Transaction Model

Further, each household has a renewable energy source that provides energy at a time slot h.

$$\phi_{t+1} = \{(\phi_t - (P_{gs} + P_s)) \vee 0\} + A_s(t) \tag{20}$$

This process is time varying and unpredictable. Demand for this energy arrives randomly according to a process $a(t)$ being the amount of energy that is requested at time *h*. Flexible loads are delay-tolerant in their electrical energy consumption patterns. The delay-sensitive or essential loads have higher service priority than the delay-tolerant loads. An optimization problem is formulated to minimize the total electricity cost and the operation delay $\Delta t_{\max}$ of flexible demands by obtaining the optimal energy management decisions [13]. Shiftable loads can be delayed into a queue within a certain time window then serviced on first come first serve basis. We define $\phi(t)$ or ϕ_t as the total queued energy requirement at time $t = h$. The total queued energy demand ϕ_t at a time t update is (20).

At each time slot *h* we use all of our renewable supply P_{re} to power the queued loads on First-In-First-Out (FIFO) basis. Should there be a shortfall from the renewables to meet the demand timeously the extra energy i.e., $P_{re} - A_e(t) - A_s(t)$ is procured from the utility grid at a cost to be minimized. The expected mean of the queued demand over a time period T is,

$$\hat{\phi} = \frac{1}{T}\sum_{0}^{T-1} E\{\phi_t\} \tag{21}$$

This is subject to, $\phi(t) \le P_{\max}$.

Typically, dissatisfaction of consumers' stems from appliances' switch-on delay, which is itself a result of service priority of hierarchical loads in residential microgrids with DSM. Therefore, energy cost minimization in such schemes should also be balanced with respect to minimizing the on-delay of appliances by adjusting the energy consumption queue according to different classes of demands. The upper bound $P_{\max}$ does not imply an acceptable limit on $\Delta t_{\max}$ the load service delay. To achieve this a modification by way of delay aware energy demand $\Im_{t+1}$ virtual queue after [6][7] is introduced in accordance with the recursive update expression,

$$\Im_{t+1} = \{(\Im_t - (P_{gs} + P_s) + \varepsilon\delta) \vee 0\} \tag{22}$$

such that,

$$\delta = \begin{cases} 1 & \phi_t > 1 \\ 0 & otherwise \end{cases} \qquad \varepsilon > 0 \tag{23}$$

The fictitious queue $\Im_{t+1}$ grows by ε if $\phi_t > 1$, i.e. queued power request are increasing. By placing upper limits on ϕ_t and $\Im_{t+1}$, then maintaining a limit on $\Delta t_{\max}$ is possible. Proof thereof is outlined in [15].

Optimization problem definition

The objective is to minimize the expected average cost of electrical energy subject to meeting essential loads and user comfort that secures a worst shiftable load demands delay whose maximum is $\Delta t_{\max}$. With this we can formulate the optimization problem as,

$$P_{av} = \min_{P_{ge}(t), P_{gs}(t), P_e(t), P_s(t)} \lim_{T \to \infty} \sum_{0}^{T-1} E[C(t)] \tag{24}$$

Subject to,

$$P_{ge}(t) + P_e(t) = A_e(t): \quad 0 \le P_{re}(t) \le P_{re,\max} \tag{25}$$

$$0 \le P_g(t) \le P_{g,\max} \tag{26}$$

Where $C(t)$ is net grid energy cost to consumer as given in (19). This optimization problem can be formulated as a multistage finite horizon i.e. $t < \infty$, discrete dynamic programing problem which can thus be solved employing backward induction dynamic programming (17) subject to the constraints set out in (14)-(16). At any given time, the system state vector is defined by the quintet, $\mathbf{x}_t = \{P_{re}(t), P_e(t), A_e(t), e_s(t), e_p(t)\}$.

Variables that can be manipulated are $\mathbf{x}_t = \{P_{ge}(t), P_{gs}(t), P_e(t), P_s(t)\}$. The backward dynamic programming induction minimization is formulated as [16];

$$\Omega(\mathbf{x}, t) = \min_{u \in \mathbf{U}} \left\{ C(\mathbf{x}, t) + \sum_{y \in Y_{t+!}} \Omega_{t+1}(y) \right\} \tag{27}$$

Where $\Omega(\mathbf{x},t)$ is the objective function at time t, $C(\mathbf{x},t)$ is the electricity cost at time t [9]. $\mathbf{U}(\mathbf{x})$ and $\mathbf{x}(t)$ define the feasibility space of control actions and states at time *t*. It is generally difficult to solve (17) dynamically with complete state, $\mathbf{x}(t)$ information. We adopt a modified Lyapunov approach to formulate an online algorithm that dispenses with the requirements of having knowledge of future states [10].

Online Distributed Algorithm Outline According to Lyapunov Method

Define a positive discrete linear system [17], where the state vector is $\mathbf{x}_t \in \Re^n$ and input control vector $\mathbf{u}_t \in \Re^m$, system matrix $A \in \Re^{n \times n}$, input weighting vector $b \in \Re^n$ and an equilibrium state $\mathbf{x}_{eq}$.

$$\mathbf{x}_{t+1} = A\mathbf{x}_t + b\mathbf{u}_t \tag{28}$$

A positive discrete time system $\mathbf{x}_{t+1} = A\mathbf{x}_t$ has a asymptotic equilibrium if and only if there exists a strictly positive vector $\mathbf{x}_t$ such that $(\mathbf{A} - \mathbf{I}_{n\times n})\mathbf{x}_t < 0$. For such a system we may choose a Lyapunov function of the form given in (29-30).

$$V(\mathbf{x}_t) = \mathbf{x}_t^T \cdot \mathbf{x}_t \tag{29}$$

or in our case from;

$$V(\mathbf{x}_t) = 1/2\left(\Im_t^2 + \phi_t^2\right) \tag{30}$$

Algorithms for queuing stability are developed by defining a Lyapunov function then employing a greed algorithm to minimize a bound on $\Delta(\Omega(t))$ (31) in every time slot [16].

$$\Delta\Omega(t) = E\left(V_{t+1} - V_t \middle| (\Im_t, \phi_t)\right) \tag{31}$$

Using the drift plus penalty function define a parameter $\Gamma > 0$ to effect the performance delay by minimizing [16] the expectation,

$$V\Omega(t) + \Gamma \cdot E\left(C_t \middle| (\Im_t, \phi_t)\right) \tag{32}$$

This function is bounded by,

$$\begin{aligned} &\Delta\Omega(t) + \Gamma \cdot E\left(C_t \middle| (\Im_t, \phi_t)\right) \le B + \Gamma \cdot E\left(C_t \middle| \Im_t, \phi_t\right) + \\ &\phi_t \cdot E\left(A_s - P_{gs} - P_s \middle| (\Im_t, \phi_t)\right) + \Im_t \cdot E\left(\varepsilon - P_{gs} - P_s \middle| (\Im_t, \phi_t)\right) \end{aligned} \tag{33}$$

Optimization of the original problem reduces to minimizing this bound according to routine in Figure. 4 below whereby the optimization is time decoupled and power meant for essential and shiftable demands also becomes decoupled. Optimization of essential load reduces to decisions on which source is to supply the essential load based on $e_p(t) - e_s(t)$ unit cost differential.

$$\underset{P_{ge}}{Min}\left(e_p(t) - e_s(t)\right) \cdot \left(A_e - P_{ge}\right) \tag{34}$$

Case Study Simulation

We simulate a prosumer with a number of selectable essential loads and suitable loads with profile similar to [13]. The hourly essential load can be easily computed. Shiftable appliances are modelled as a collection of independent and identically distributed (IID) random variables as each random variable has the same probability distribution as the others and all are mutually independent. We take utility electricity cost as $e_g(t) = 1.4$ per unit from 0800 to 0000Hrs and $e_s(t) = 1.25$ per unit from 0000Hrs at night to 0800Hrs. Feed-in tariff is set as $e_p(t) = 1.3$ per unit during daytime and $e_p(t) = 1.15$ per unit at night.

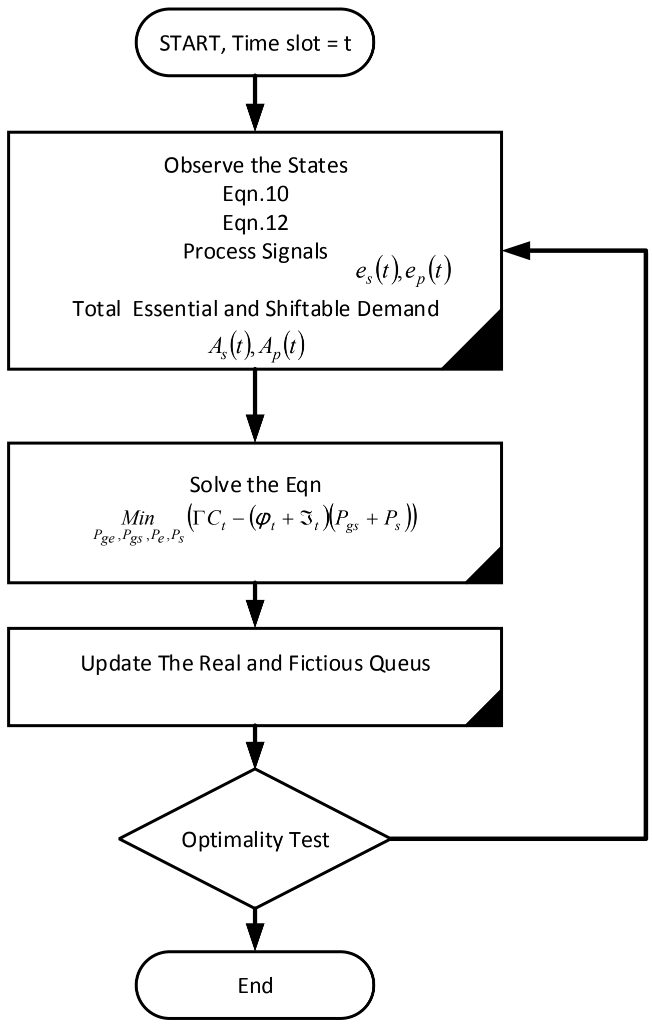

Figure 4 Optimization Flowchart

We compare the proposed prosumer two way energy flow transaction scheme with the Lyapunov optimization and a strategy of purchasing all the available renewable resource and only buy from the grid when if the produced renewable energy $P_{re}(t)$ cannot meet the essential $A_e(t)$ and shiftable $A_s(t)$ demand. Figure.5 depicts electricity costs for above transaction schemes. It can be seen that costs associated with two-way transaction scheme is less than purchase only strategy. With RES and optimization schemes prosumers can sell some renewable energy to the grid and they are also able to reschedule loads to favourable periods with lower tariffs.

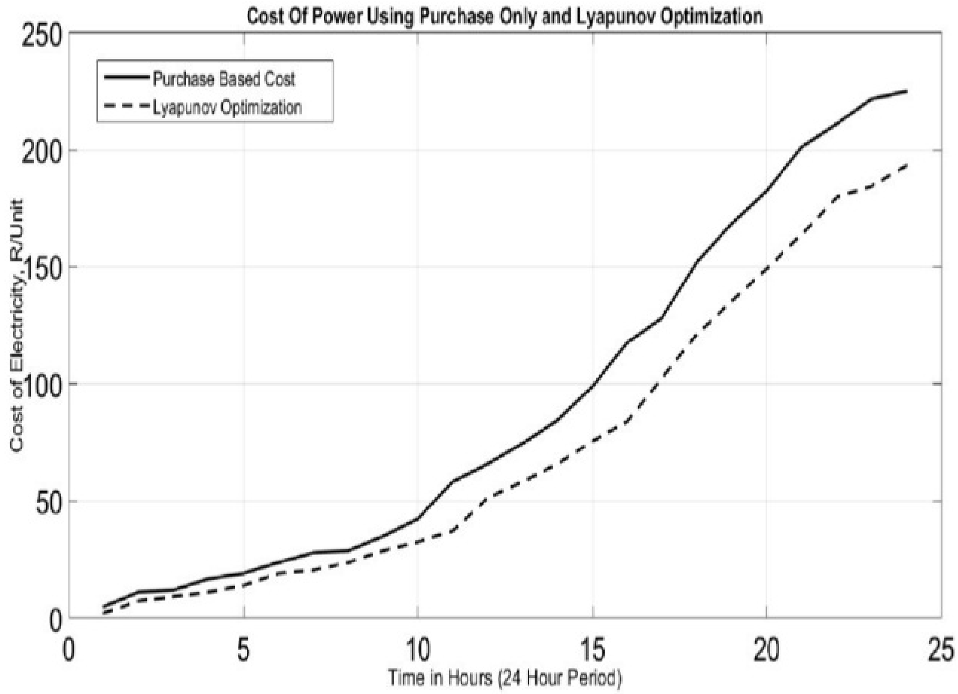

Figure 5 .Cost comparison of direct purchase and Lyapunov optimized strategy

Conclusion

The paper has demonstrated a promising outlook to empower prosumers with means to manage their loads in such a way that they take advantage of 'free" REG, and also attractive off-peak utility tariff regimes. Categorization of household load into essential and shiftable loads allows practical scheduling with priority queue to be set up. To meet acceptable levels of convenience shiftable loads are queued in a time bound queue whereby they are met or satisfied within a predetermined time limit which limit talks to consumer satisfaction. The right mix of energy from the grid, sold to the grid is obtained from a Lyapunov based optimization routine which time decouples the essential and shiftable loads. Simulation results suggest possible servings as result of the optimization routine when compared to a direct strategy of purchasing power to meet demand shortfall without any recourse to smart scheduling. The main challenge for successful operation and implementation of such strategies is the wide spread adoption of smart metering technology coupled with automatic load management in such a way that consumer convenience is preserved as far as possible.

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